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A Forecasting Approach to Improve Logistics Planning in the Colombian Air Force

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THESIS

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Daniel A. Melendez

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Abstract

The Colombian Air Force recently installed a logistics operating system to improve the logistics system. However, the inventory cost and turnover have not stopped growing; subsequently, the operational readiness has been affected. The purpose of the study was to compare the performance of several forecasting techniques to improve the current planning process of aircraft parts in the CAF. The research used five phases.

The first phase identified the relevant factors and the forecasting techniques selected for the experiment. The factors were repairability, demandability and uniqueness. The forecasting methods were single and double exponential, moving average, autoregression and linear regression. The third and fourth phases simulate additional demand data. It was found that single exponential and moving average perform better than the others. The fifth phase found that the forecasting system can provide substantial savings to the logistics system.

Finally, it can be concluded that demand for most spare parts cannot be predicted because forecasts always contain errors. Then, it is necessary to consider additional improvements in logistics operations to make it easier to live with demand uncertainty. Among such improvements would be a shortening of the resupply time, the procurement lead time, and of the repair cycle for spare parts.

A FORECASTING APPROACH TO IMPROVE LOGISTICS PLANNING IN THE COLOMBIAN AIR FORCE

I. Introduction

In recognition of the importance of effective and efficient procurement of aircraft parts, this thesis presents a quantitative analysis of the use of forecasting techniques to predict future logistics requirements for the Colombian Air Force (CAF). This chapter justifies the analysis by presenting the major issues surrounding logistics in the Colombian Air Force, such as aircraft operational readiness, inventory investments, and inventory turnover. The chapter then provides the rationale for conducting a quantitative study to predict future requirements in the CAF logistics system. The research problem, objective, and investigative questions follow. Finally, we provide a summary of the methodology employed with a description of its scope and limitations.

General Issue

Through the years, the Colombian Air Force (CAF) has developed its own logistics system. This system consists of a Logistics Headquarters with its directorates of maintenance, supply, foreign market, armament, and purchasing. The logistics process control is centralized at the CAF headquarters, but the execution is decentralized at the operational air commands. The budget for the entire operation is annually assigned and divided in accordance with the customer's requirement. In the earliest 1990's the CAF logistics statistical results [EMA3 03-98, 1998] showed some improvement in the rate of aircraft readiness but responsiveness was not enough to cover the operational requirements. Another result showed an approximate 100% increase in average inventory cost. At the same time, the inventory turned over approximately once every four years. In addition, the annually allocated budget was insufficient to increase aircraft readiness.

Under this situation, the CAF ordered a complete revision of its logistics procedures to find the common cause for these results [JET 01-97, 1997]. The investigation concluded that several issues were affecting the process. First, there is a difficulty in sharing logistics information within the logistics process. Second, the reliability of logistics information, especially related to historical records and spare parts consumption, is not good enough to enhance the logistics process. Third, there are no standard procedures to plan future requirements of aircraft spare parts. Finally, the work-order process is not used to initiate corrective and preventive maintenance activities. Because of this evaluation, the CAF bought a logistics information system, EQUALS, to be implemented in 1998.

Research Problem

The CAF recently installed a logistics operating system, EQUALS, to improve communication, reliability, flexibility, and accuracy of the logistics information flowing through the supply channel. However, the initial results showed that the inventory cost and turnover have not stopped growing; subsequently, the operational readiness has been affected by the lead-time within the supply channel. This is a problem because budget allocations require accurate estimates of the product volume to be handled by the logistics system. Under certain circumstances, especially during short term planning such as inventory control, logisticians often find it necessary or useful to produce forecasting information [Ballou, 1992:108-109].

Purpose of this Research

The purpose of the study is twofold. First, this thesis will compare several forecasting techniques to be used with consumable and repairable items. The second purpose is to provide a procedure for the Colombian Air Force to plan future aircraft spare parts requirements based on forecasting techniques using the information provided by its logistics information system.

Contribution for the Colombian Air Force Logistics Managers

The purpose of this research is to provide the CAF a forecasting approach to plan future aircraft spare parts requirements. This approach provides the CAF and the "Jefatura Técnica" (Logistics headquarters) with the following contributions:

1. Improve procurement decisions of future requirements. The implication of this contribution is that forecasting techniques will allow managers to understand demand patterns and concentrate efforts in developing and improving forecasting techniques in other areas of the organization.

2. Improve operational readiness. A robust forecasting system will improve the operational readiness because of the accuracy of the spare parts planned to have in inventory.
3. Improve budget allocations. The implication associated with the budget is that a good forecasting estimate increases the cost effectiveness ratio. The cost effectiveness ratio is defined in terms of every "peso" ($ 1.00 dollar = $1,300.00 pesos) invested per flying hour.
4. Improve inventory turnover. Developing a reliable and accurate forecasting system will allow the CAF to increase the inventory turnover gradually by reducing the average inventory and increasing the sales.
5. Observations on the forecasting approaches' weaknesses and strengths. The implications associated with this contribution are that managers will have a greater understanding of and confidence in forecasting techniques.

Research Question

Ballou suggests that the forecasting of demand levels is vital to the firm as a whole as it provides the basic inputs for the planning and control of all functional areas, including logistics, marketing, production and finance [Ballou, 1992: 108-149]. In this case, forecasting is studied as an important aid in effective and efficient planning in the CAF logistics environment. The research questions are as follows:

1. Can forecasting techniques improve the planning process of future requirements for aircraft spare parts with the current information provided by the CAF logistics information system, "Equals"?
2. What forecasting technique is more appropriate for each demand pattern category?

Research Hypotheses

To answer the research questions, a factorial experiment will be conducted to measure the performance of several forecasting methods on several types of demand patterns. The hypotheses to be tested are that forecasting methods can improve supply performance, and that forecasting techniques do not work equally well on all demand categories.

$H1_o$: No performance difference exists between forecasting techniques and current demand management techniques.

$H1_a$: At least one forecasting method is different from current demand management techniques.

$H2_o$: No performance differences $F_1 = F_2 \ldots = F_n$ in all demand categories.

$H2_a$: At least one forecasting technique differs from others.

Research Approach

Three phases will be used to evaluate the logistics requirements using different forecasting techniques with the data provided for the experiment.

The first phase is to identify the characteristics of the aircraft spare parts demand pattern and determine the forecasting techniques to be used during the study. This phase includes the following specific requirements:

1. Categorization of CAF spares in terms of critical factors in demand patterns.
2. Select a sample of aircraft spare parts to be used in the experiment based on the critical factors.
3. Select a time horizon to forecast.
4. Determine the forecasting techniques to be used during the experiment.

The second phase of the experiment consist of measuring the performance of the forecasting methods. This phase include the following specific requirements:

1. Perform forecasting on the spare parts selected for the experiment.
2. Perform a general factorial procedure to provide an initial analysis of the dependent variable, the forecasting error, affected by the factors and the treatments.
3. Perform the appropriate statistical tests to determine if there are any differences in the performance of the forecasting methods.

The third phase consists in prepare and perform the simulation experiment. This phase includes the following requirements:

1. Conceptualization of the model to be used during the simulation process.
2. Analysis of the data to be used in the experiment.
3. Verification and validation of the simulation model.

4. Production runs, and their subsequent analysis to estimate the measures of performance.

Scope and Limitations

The sample to be analyzed is a convenience sample because the actual Air Force data is in the process of migrating to its new logistics information system. There were some obvious limitations to the data. First, the data analyzed by aircraft model consisted of demands generated by 8 aircraft at only one geographic location. Secondly, the detailed knowledge of individual parts present gaps in information for all the demand data studied. The gaps represented are on applicability of parts to aircraft, relationship between part numbers including information on interchangeable parts, substitutable parts, parts that are component of a higher assembly, and parts that are independent in an operational sense.

Another deficiency in the data studied is that some additional major maintenance was performed to the Bandeirante and the Fokker during the period covered by the data; but it was not documented properly. For certain parts, this maintenance appears as a normal consumption; thus, it is affecting the demand patterns during the period being investigated.

Finally, some unit cost for the Dash 8 repairable item approximates the real repair cost, since most of the unit cost for the items issued represents the leasing value. However, this cost data has no effect on the underlying distribution of the demand for spare parts.

Assumptions

The analysis of this research adopt the following assumptions:

1. The sample presents a similarity with the CAF in maintenance and supply procedures.
2. Similar time series components between the commercial airline and the CAF.
3. The unit cost of each item was provided in "pesos" (Colombian currency), the transformation to dollar value was based on $US 1.00 equal 1,300.00 "pesos".
4. The repairable unit cost of the Dash 8 in some cases approximate the repair cost because the price used is the leasing value but not the repair cost.

Chapter Summary and Organization of the Research.

This chapter presented the reader with the environment of the research, the specific problem, the research purpose, the research and investigative questions, the managerial contributions, the hypothesis, the scope and limitations, and the underlying assumptions. Chapter II describes the critical issues in the logistics channel, the current forecasting concepts, and the type and characteristics of demand patterns. Chapter III discusses the research methodology. Chapter IV presents the results and analysis of the data collected. Finally, Chapter V provides the conclusions and recommendations derived from the research.

II. Literature Review

Introduction

This chapter discusses the significant issues in logistics, the current forecasting concepts, the nature of aircraft spare parts demand, and the logistics system related to the research problem. First, the chapter gives a description of the critical issue in a logistics environment. Second, the chapter describes the Colombian Air Force logistics system. Third, the chapter provides the main characteristics of the CAF logistics system, EQUALS. Fourth, the chapter introduces the most useful forecasting techniques appropriate for the research environment. Finally, it describes the measures to achieve forecasting accuracy.

The Importance of Logistics

According to Lewis and Talalayevsky [1997:141,157], logistics is the discipline that studies the flow of goods and services, and accompanying information within and between organizations. The essential issue in logistics is the coordination among all the activities.

The first consideration for management is to decide the strategic direction for a company; it means to "see the big picture" [Casper, 1997: 175-178]. This overall direction is outlined and translated into a corporate plan of action. The corporate plan is then divided in sub-plans for the functional areas of business, such as marketing, production, and logistics [Ballou, 1992:29-49]. The corporate plan regarding logistics includes decisions in locating warehouses, setting inventory policies, designing order systems, and selecting modes of transportation. Having this framework, the logistics strategy has three objectives: cost reduction, capital reduction, and service improvements.

Research suggests [Razzaque, 1997:18-38] that before starting to deal with logistics systems, it is advisable to study your own country's logistics system (where the firm is growing). This logistics approach could be useful for less developed countries. An important issue in this analysis is to understand that the sophistication level of the logistics system evolved within a firm is essentially a micro-system built on the basic framework of the nation's macro logistics. If a country does not have a good base network of dependable transportation, warehousing, communication and other related facilities, desired configuration of the network will be difficult. The challenges in many less developed countries are to develop a logistics system, mainly by management involvement and logistics education. Literature reveals that in those cases an anticipatory logistics plan could alleviate the inefficiencies.

Ballou [1992:29-49] and Abouzolof [1997:2-9] state that once the strategic direction has been defined, then the priority is to plan the logistics activities. One way to look at the logistics-planning problem is to view it in the abstract as a network of links and nodes [1992:29-49]. Links represent the methods for transmitting information from one geographic point to another. Nodes are the various data collection and processing points. Information for planning is derived from sales revenue, product costs, inventory levels, warehouse utilization, forecast and transportation rates [Ballou, 1992 p: 29-49].

Mentzer [1994: 215-227] states that the information system is a component of the logistics control system and should provide relevant information to the logistics manager. In the next century the need for more accurate, comprehensive, and timely control systems will become highly pronounced. In addition, the logistics organization will focus more on customer satisfaction and resource management.

Other studies [Closs, 1997: 4-17] by logistics experts representing the world class logistics organizations, suggest that the logistics operating and planning systems are highly valued. There is also empirical evidence to support that logistics operating system (LOS) and logistics planning system (LPS) assessments are predictive of overall logistics competence. LOS includes transactional applications such as order entry, order processing, warehousing, and transportation. LPS includes coordinating applications such as forecasting, inventory management, and distribution requirements.

Other experts [Bardi, 1994: 71-83] argue that logistics information systems (LIS) are a powerful approach to deal with the business diversity by optimizing logistics costs, customer service, information integration, and customer linking. These experts also identify the relationship between corporate logistics goals, competitive environment, and the strategic importance of information to top management supporting the LIS.

Sengupta [1996:28-33] for example presents the areas of forecasting, purchasing, production, storage, and distribution as potential improvement in a logistics environment. Korpela [1996: 169-168] suggests that one of the most important issues for a good inventory management is to have a demand forecasting capabilities for the basis of planning of production, transportation, and inventory levels.

One good example [Martin, 1997:54-58] of using the demand projections, inventory strategy, and streamlining the supply chain is the experience done at Xerox Corporation. With this information, the benefits obtained at Xerox Corporation were the inventory reduction, the increase in product support, and high customer service.

Mecham [1997: 78-79] presents another case used by AlliedSignal Aerospace's worldwide repair and overhaul network to improve its logistics system. By means of new software, AlliedSignal's active inventory is maintained at minimum, while ensuring the orders are filled promptly. This software provides a new tool to forecast demand, plan inventory levels, and allocates distribution of its spare, repair, and upgrade parts. The AlliedSignal's essential issue is better planning, not necessarily a means to improve forecasting. The critical point is knowing which parts you have to deal with, when you have to deal with the suppliers, and what actions need to be taken.

The Colombian Air Force Logistics Environment

The Colombian Air Force has been in operation since 1919 [FAC, 1985:2]. Its operational bases are located all around the country, where the weather can be highly variable, sometimes presenting extreme differences of temperature, humidity and salinity. The CAF consists of 12 Operational Bases [JOA 12-97, 1996: 2-10], including the Military Academy and one Repair Maintenance Facility similar to a depot in the U.S. Air Force. The CAF includes airplanes and helicopters from different countries around the world. Some aircraft were manufactured in the United States, others in France, Spain, Brazil, Israel, Russia, and Holland. The logistics system to support the operational flying requirements is organized under one large logistics agency, named "Jefatura Técnica" (Logistics headquarters) and six directorates [Manual de Mantenimiento, 1994:4-45]. These directorates are maintenance, supply, foreign market, purchasing, armament, and education and technical training. This organization also includes a staff for planning, special projects, and quality control as well.

Logistics Issues

For the purpose of this research, the issues to be addressed related to the logistics problem will be concerned only with those that are affecting the inventory cost, inventory turn over, and readiness.

The complexity of the logistics activities was mainly caused by the fact of many foreign aircraft manufacturers: The United States, France, Holland, Spain, Israel, Brazil and others. This factor includes frequently dealing with and handling different languages, procedures, and regulations.

Another logistics problem is the purchasing process of new or used aircraft spare parts [Suárez, Interview, 1998]. This process has to deal with the long period required in some cases for the manufacturer to process the requisition. If the part requested is a high demand item, the lead time between the time the requisition is issued to the time it is received in Colombia is about 3 or 4 weeks. If the part requested is a low demand item, and if it requires a special production order, the lead time will be higher than 40 weeks. In some cases, this lead time can be up to 80 weeks.

The process to repair aircraft spare parts at intermediate or depot level [Melendez, D. 1996, 30-50] is another issue to be considered. This process can be performed in two ways. One option is to repair the item at the CAF depot; the second option is to send the part to be repaired in a foreign country. The repair process at the CAF depot is also affected by the purchasing process described previously; on the other hand, the estimated provisions for spare parts at the depot include the need to request well in advance the material required to perform the level of repair required. The lead time in this case can be up to 3 or 4 years. The second option, send to a foreign country, is affected by the CAF purchasing process and the scheduling availability at the supplier shop. The lead time in this case ranges from several weeks to 2 or 3 years.

The estimation of provisioning of aircraft spare parts, consumable and repairable, is based on historical data, on technical experience, or actual needs [Bohórquez, 1997]. However, in most of the cases [Suárez, 1995: 52-53], this estimate is based on the judgment and experience of the people involved at all levels, rather than on reliable data and quantitative methods.

The Inventory Problem

The inventory issues can be viewed from two different angles [Melendez, D. 1996:80-85], inventory cost and inventory turn over; however, these two measures are related. The aircraft manufacturer diversity, the purchasing process, the repair process, and the prediction of future needs are the drivers for the high inventory costs, which in turn affect the inventory turnover. Table No.2 shows the inventory costs, the average inventory, the purchases and sales, and the inventory turnover in 1995.

Table 1. Inventory Costs in 1995 at the Colombian Air Force

Operational Group	Initial inventory	Total Purchases	Total Sales	Final inventory	Average inventory	Inventory Turnover
Depot	$4.50	$7.30	$2.64	$9.16	$6.83	0.39
Tactical	$0.49	$1.02	$0.30	$1.21	$0.85	0.35
Academy	$1.31	$2.12	$0.73	$2.70	$2.00	0.36
Transport	$4.50	$9.20	$1.87	$11.83	$8.17	0.23
Helicopters	$9.29	$16.00	$6.75	$18.54	$13.91	0.49
Fighters	$9.92	$19.16	$4.38	$24.70	$17.31	0.25
Total	**$30.01**	**$54.80**	**$16.67**	**$68.14**	**$49.07**	**0.34**

Note: Values are approximation in millions of dollars [Meléndez, D. 1996: 25]

The statistics during 1995 show in summary that the inventory cost grew up approximately 127% (US$38,100,000.oo) with respect to the initial inventory. During this period the inventory turnover was very low, 0.3 turns per year. If sales remain constant and no additional purchases are needed, the CAF will need approximately 4 years to renew the total inventory [Melendez, D. 1996: 86]. However, these conditions are almost impossible to achieve. Therefore, it seems more real to state that the CAF inventory will continue to grow in the following years.

The CAF Budget Preparation and Allocation

The budget assigned for purchasing provisioning spare parts is prepared two years in advance [Suárez, 1998]. Then, the budget is allocated to the operational units; however, almost 80% of total procurement of aircraft spare parts is executed directly by the logistics headquarters because of the bureaucratic organization model followed by the CAF, as well as the lack of infrastructure at the operational bases.

The budget preparation [Suárez, 1995:46-53] started in August, 18 months before it is allocated, with the publication of a general directive by the Minister of Defense

(MOD) to be complied with by Military Branches (Army, Navy, and Air Force) and National Police. Once the directive is received at each branch, it is relegated to the operational units.

When the operational units receive the budget directive, they have to prepare the budget required for its needs for a point located eighteen (18) months in the future. The budget required is prepared at the operational units and is sent to their respective headquarters by the fourth month (November).

Each headquarters revises the operational unit proposals and in month six (January), present a consolidated budget to the Air Force Chiefs of Staff for his approval. With the budget approved by the Air Force, it is sent to the Joint Chiefs of Staff in month seven (February).

Then, the financial Budget Division [Suárez, 1995:41-46] at the MOD consolidates the proposals received for all the Military Branches no later than month eight (March). By month nine (April), the financial Budget Division submits the defense budget to the Ministry of Finance and to the National Planning Department.

In month twelve (July), the Defense budget with the other budgets prepared by the other ministries and departments are submitted to the Congress for its approval. The budget is studied at the Congress and between month 14 and month 15 (September and October) is submitted to the President.

The President receives the budget approval from the Congress no later than month fifteen (October); then he has 30 days for its acceptance. Under normal circumstances, the President must sign the Budget Law on month sixteen (November). If for any reason, the President does not accept the Budget, it is returned to Congress for corrections. Later, by month seventeen (December), the revised budget is sent back to the President for his acceptance. Once the President signs the budget law, the budget becomes available to spend by the Colombian Air force in month eighteen (January).

Aircraft Readiness

This readiness is calculated on the daily basis with information provided by the operational units. The readiness calculation only includes the aircraft ready for flight, and the ones that are in corrective and scheduled maintenance activities. As a part of the scheduled maintenance, the aircraft in major or depot maintenance, and those undergoing a major modification are not counted for the calculation [Manual de Mantenimiento, 1994: 35].

The aircraft readiness at the CAF is measured as the number of aircraft ready for flight per day, or month. Then, at the end of the year the "Jefatura Técnica" presents a readiness average for operational unit, for type of aircraft, and a general readiness average for the CAF [Manual de Mantenimiento, 1994: 35].

These measure of performance is used to quantify the maintenance tasks performed at each operational unit. The goal established by the Colombian Air Force headquarters is to achieve 80% of readiness, which is considered enough to cover the operational requirements [Gil, 1998: 2]. As an example of the readiness achieved by the Colombian Air Force, the average during the last 7 years has been almost 60%. During the period 1990 to 1995, the average readiness for the CAF was 54% [Meléndez, D. 1995: 56], then for the following two years the average readiness increased to 62%.

The Colombian Air Force Logistics Information System – EQUALS.

The logistics information system used by the Colombian Air Force is an aviation management software. This logistics information system is called EQUALS [http://www.equals.net]. EQUALS is a system that allows the CAF to integrate some of the logistics aspects under a centralized database located at the CAF headquarters. The main function of this system is to provide total visibility of the logistics aspects, such as aircraft maintenance, spare parts purchase, and spare parts inventory, to enhance decision-makers ability to improve customer service, reduce costs, and improve internal communications.

The customer service is improved by providing accurate and timely information to the operational bases as well as the CAF headquarter. The cost can be reduced through more effective inventory management, improved scheduling of aircraft and tracking aircraft availability, while providing accurate information from reports and charts to assist in management decisions. The internal communication can be improved by providing a single common source of data and support for information exchange between all users by means of an integrated electronic mail capability.

Module Components

EQUALS [EQUALS home page, 1997] comprises four modules: the inventory and warehousing operation module; the aircraft maintenance module; the international purchases module; and the employee module, to integrate the CAF logistics system.

The inventory and warehouse operation module includes: point-of-sale data, purchase orders, delivery order tracking, vendors, configuration tracking, categories, and departments. This module provides “stores support” which permits the CAF to control all facets of inventory and warehouse management. Vendors have access to the system and consumables and repairables can be tracked in any form or quantity desired by the user. This data can be used to forecast demand and establish optimum stocking levels. All aircraft spare parts issued against any work order are accumulated in the system. A point-of-sale module provides the ability to inventory and track sales of any aircraft spare parts consumed by the CAF. In addition to this module, the system is able to provide a customizable flight hour cost based on the flying activity and spare parts consumption reported for the operational units.

The maintenance module is designed to provide accurate information regarding aircraft operating times and cycles, recurring maintenance tasks, service bulletins and airworthiness directives. Because EQUALS is an integrated system, all modules provide maintenance parts usage as the flight information is updated. Scheduled maintenance, tool calibrations and inspections are tracked in EQUALS, providing a complete reports system including any spare part with serial number, preventive and corrective maintenance actions and inspection reports. In addition to this module, work orders and time sheets for maintenance can be generated, with job assignments limited only to those employees showing technical skill status in the employee module.

The employee module provides the ability to enter data for every employee with required qualification status in the CAF according to internal policies. This module allows qualified individuals for assignment to certain maintenance tasks, using a certification database, and tracks individual training.

The purchasing module is designed to exercise control over the international logistics and acquisition process. It includes continuous tracking on the repairable and consumables purchasing process, the aeronautical parts nationalization process, the supplier contracts, payments, and customs fees. The input concerned with the tracking of purchases out of the country is updated daily from the CAF purchasing agency located in Fort Lauderdale, Florida, USA. This module allows the logistics Headquarters to monitor the purchase status at any given point, but does not include transportation activity.

Implementation Plan

The CAF acquired the system in the first quarter of 1997 to solve the lack of total visibility of the logistics map and to improve internal communication between the logistics agencies. This software is planned to be implemented in phases [Butler: 1998]. The first phase consists of gathering the actual information used by the software and to train the personnel involved in the implementation process. The second phase includes the installation of the main terminal computer at the logistics headquarters as well as the first node at the "Comando Aéreo de Transporte Militar" (Military Air Transport Command). Additionally at this phase, a node at the International Air Force Purchasing Agency will be installed. The third phase consists in the activation of the second node located at the "Comando Aéreo de Mantenimiento" (Depot Maintenance Command) and to setup the internal communication capability with the main terminal and between each node. The fourth phase consists of the activation of the remaining nodes located in the other logistics agencies involved with the maintenance and supply activities.

The complete implementation of this logistics information system is expected at the end of December 1998. After that, six months of operational tests will be conducted with all the module interacting with each other to assess the real capability of the new system.

Why Forecasting?

The main reason for planning is to account for lead-time and rapid changes in procurement costs [Abbas, 1996:131-150]. It assumes that there is a time lag between awareness of an impending event or need and the occurrence of that event. In such situations, Makridakis [1998: 2-19] states that forecasting is needed to predict when an event will occur, or a need arise, so that the appropriate actions can be taken. Planning is important because the lead-time for decision making ranges from several years to few days, hours, or seconds. In this case, forecasting is an important aid in effective and efficient planning.

Most writers [Makridakis, 1998: 2-19] agree that both forecasting and planning concern themselves with the future. It is important to integrate these two functions within the organization. Knowledge of forecasting techniques is of little value unless they can be effectively applied in the organization planning process. That knowledge includes an examination of the planning activities within an organization so that the types of forecast required and the techniques available for providing them can be tailored to the organization's need.

According to Makridakis [1983:809] forecasting is the prediction of values of a variable based on known past values of that variable or other related variables. Forecasts also may be based on expert judgements, which in turn are based on historical data and experience. In a later source, Makridakis [1998: 2-19] states that the areas in which forecasting plays an important role are scheduling, acquiring resources, and determining resource requirements.

Ballou [1992 p: 108-140] states that the need for demand projection is vital to the firm as a whole, and some predictions are used for inventory control, economical purchasing and cost control.

According to Sengupta [1996:28-33] some of the benefits obtained when using forecasting are the removal of organizational and functional barriers, early visibility to changes in demand, and a single set of plan that drives and integrates the information across the supply chain.

Why Forecasting at the CAF?

Studying the series of logistics issues affecting the performance of the logistics process at the Colombian Air Force, it is not obvious that forecasting techniques can produce benefits to the entire system. To focus the problem it is useful to establish the causes surrounding the biggest issues affecting their ability to maintain a lower level of inventory and a higher aircraft availability. The challenge is to decrease inventory, increase readiness, and at the same time avoid waste in the budget. The problem was organized using a causal map to identify if the forecasting decision would lead the CAF to success.

A cause and effect diagram [see Appendix A] eased the task of identifying what the core problems in CAF logistics were. A review of the specific problems was rewritten as possible management objectives relevant to the overall situation. After that, the objectives were arranged according to causes and effects.

After examining the possible causes and effects, the causes were ranked in accordance to the one that produces higher weight towards addressing the CAF concern. The CAF concerns were related to decreasing inventory costs, increasing readiness and avoid budget waste. In addition, the major causes were the ones that produced most of the effects through the map. Major and minor causes are identified in the causal map. The minor causes were related with time span used to allocate the budget, the multiple countries involved in the logistics system, the different languages to deal with, the wasted resources due to a bad planning, and the period of time required to process a spare part.

Among the major causes, the following were the most representative of this particular problem. First, there is no policy that would keep a certain quantity of parts as a safety stock. Second, the poor quantitative decisions tool used for the people working at the Supply Directorate caused the inventory to increase. Another cause was the absence of a standardized plan able to identify in advance the possible aircraft spare parts required in the future. This last root cause could be addressed by the implementation of a planning or forecasting system.

To summarize, the biggest problem the CAF was dealing had to do with the inaccuracy of the information they were using. This fact affected the planning capability of the organization, making the budget insufficient enough to increase aircraft readiness.

After studying the causes and effects, the root cause of all the CAF symptoms was as a lack of information. Specifically, a lack of right information, for the right person to take the right decision. The purchase of the logistics information system, EQUALS, would enormously help the CAF to solve its problem. However, this logistics information system is a logistics operating system and not a logistics planning system. Therefore, it seems that establishing a forecasting procedure using the information produced by EQUALS would address the other root cause and produce an effect on inventory cost, aircraft readiness and budget waste.

Forecasting Methods For Spare Parts

A variety of forecasting methods are available to management [Makridakis, 1998: 2-19]. These range from the most naïve methods to highly complex approaches such as neural nets and econometric systems of simultaneous equations. There are several forecasting techniques: quantitative, qualitative, and unpredictable methods. Quantitative methods can be used when sufficient quantitative information is available. They predict the continuation of historical patterns, and are useful to understand how the presence of some variable affects the behavior of others. Qualitative methods can be used when little or no quantitative information is available, but sufficient qualitative knowledge exists. Unpredictable methods can be used when little or no information is available.

According to Dussault [1995: 9] the U.S. Navy and Air Force approach uses a variety of forecasting techniques to predict demands. Managers may select a certain forecasting technique depending on the pattern projected by the data.

The Requirements Data Bank System (RDB) used by the U.S. Air Force uses four different forecasting techniques [Dussault, 1995:10]: moving average (four and eight quarters), double exponential smoothing, linear regression (known as PRELOG), and manually input estimates (primarily used for new items). The USAF relies on the eight quarter moving average technique for two reasons: it is user friendly and the technique provides stable forecasts under fluctuating demand.

The Statistical Demand Forecasting System (SDF) used by the U.S. Navy [Dussault, 1995:11], uses various forecasting techniques such as exponential smoothing, double exponential smoothing, moving average, linear regression and non-parametric methods.

Although both forecasting systems have several forecasting techniques, the technique used approximately 90% of the time by both services is the moving average forecasting [Dussault, 1995: 9].

Another study [Clay, 1997: 817-823] in the manufacturing and re-manufacturing industry analyzes methods of managing the supply chain of automotive service parts. This study describes the use of simulation to evaluate various parts forecasting and level setting strategies for automobile dealer inventories. Four different forecasting algorithms were evaluated. They were the single exponential smoothing, double exponential smoothing, bayesian, and simple moving average. Clay suggests that exponential smoothing overestimates sales of the erratically demanded parts which dominate dealer inventories. The bayesian method was found to be more effective in forecasting this erratic demand for slow moving parts. The principal weakness of the bayesian method is that it requires historical sales data analysis and careful selection of an appropriate probability distribution of sales. According to analysis of part sales history and other published works, it is assumed that slow moving parts demand follows the negative binomial probability distribution, for which variance is strictly greater than the mean [Clay, 1997: 821]. This study also found that all methods perform similarly at very high fill rate levels when days of supply was reduced from 45 days to 27 days. Once days of supply falls below 27, the simple moving average and the bayesian method provide higher fill rates than all others. This performance comes with a high price. Both the simple moving average and the bayesian method require a substantially larger inventory investment than the two exponential smoothing methods.

Abbas and Hirofumi [1996: 131-150] present an integral framework for forecasting and inventory management of short life cycle products. These products are becoming increasingly common in several industries. The research was motivated by the experiences of a personal computer (PC) clone manufacturer. This industry is characterized by a quick assembly after receiving customer orders, no finished goods in inventory, fast and timely deliveries, and component procurement costs account for 80 to 90% of all product costs. Also, the cost of key components declines over time, delivery lead time for major components can be as high as six months, and the demand for products is highly seasonal.

Under the circumstances given, a useful forecasting system must accommodate the unique characteristics of the short product life cycle environment described before. First, because of the rapidly changing procurement costs, accurate medium-term (monthly and quarterly) demand forecast is necessary for a cost conscious procurement plan. Second, since the procurement lead times are very high, the forecast must be made fairly in advance of the product's introduction. Third, by the time a significant demand history is available, the product may be well into its maturity phase. These factors preclude the use of traditional forecasting methods such as the moving average, smoothing, and the Box-Jenkins ARIMA models [Abbas, 1996: 140].

Instead, Abbas proposes the use of the bass diffusion model, which is a seasonal trend growth model. It is important to mention that the behavioral assumptions underlying the bass model are relevant only in a monopolistic situation and several other factors affect the process of diffusion. Primarily the S-shaped curve and parsimony of the model influence the choice of the bass-type growth model. Abbas also notes that the firm under consideration dominates specific market segments with an unmatched price/quality/service advantage. This observation lead to the hypothesis that a monopolistic curve like the one used in the bass diffusion model may be applicable [Abbas, 1996: 144].

The main advantage of this model is that it can be used to forecast sales in the absence of a sales history. For short life-cycle products, the optimal life-cycle procurement problem under demand uncertainty is addressed by incorporating the uncertainty within the parameters of life-cycle cost growth, and for short life-cycle products that exhibits seasonality [Abbas, 1996: 146]

Forecasting Algorithms

The most common forecasting techniques used to predict demand for spare parts in the U.S. military, and in the two manufactures and remanufacture industries are summarized in table 2:

Table 2. Most Common Forecasting Techniques Used for Spare Parts

Forecasting Technique	US Air Force	US Navy	Automotive Service Parts	P.C Computer Clones
Moving Average	X	X	X	X
Double Exponential Smoothing	X	X	X	
Single Exponential Smoothing		X	X	X
Linear Regression	X	X		
Non-parametric		X		
Bayesian			X	
Bass Diffusion Model				X
Box-Jenkins ARIMA Models				X

For the purpose of this study, the forecasting techniques to be discussed are those that are related to the aircraft industry and manufacture and remanufacture industry. Therefore, the focus will be on the moving average, single exponential smoothing, double exponential smoothing, ARIMA, and linear regression.

Exponential Smoothing. Probably the most useful technique for short-term forecasting is exponential smoothing [Ballou, 1992:117-118]. It has been observed to be the most accurate among competing models in its class for many applications. It is a type of moving average where the past observations are weighted more heavily than less recent observations. The weighting scheme can be reduced to the following expression involving only the forecast from the most recent period and the actual demand for the current period. Thus, the formula for exponential smoothing is illustrated in Equation 1.

$$F_{t+1} = \alpha A_t + (1-\alpha)F_t \tag{1}$$

where

F_{t+1} = Forecast for period following t, or next period

t = Current time period

A_t = Demand at period t, or current period

F_t = Forecast for period t, or current period

α = Exponential smoothing constant ($0<\alpha<1$)

Choosing the proper value of the weighting factor α depends on the weight placed on the demand levels. The higher the value of α, the greater is the weight placed on the most recent demand level. This higher value allows the model to respond quickly to changes in demand levels. On the other hand, the lower the value of α, the greater weight is given to demand history through the previous forecast in forecasting future demand and the longer is the time lag in responding to fundamental changes in the demand level.

Double Exponential Smoothing. According to Hanke and Reitsch, 1992, from Dussault, [1994: 13-14] the double exponential smoothing technique used by the US Air Force is the "Brown" method. It is used for forecasting demand data that have a linear trend. The formula for the double exponential smoothing [Makridakis, 1983: 93-95] is illustrated in equation 3 to 7.

$$S'_t = \alpha X_t + (1-\alpha)S'_{t-1} \tag{2}$$

$$S''_t = \alpha S'_t + (1-\alpha)S''_{t-1}{}' \tag{3}$$

$$a_t = S_t' + (S_t' - S_t'') = 2S' - S_t'' \tag{4}$$

$$b_t = \frac{\alpha}{1-\alpha}(S_t' - S_t'') = 2S' - S_t'' \tag{5}$$

$$F_{t+m} = a_t + b_t m_t \tag{6}$$

where

b_t = Computed value for t

a_t = Computed value for t

F_{t+m} = Forecast value

S'_t = Single exponential smoothed value

S''_t = Double exponential smoothed value

α = Smoothing factor (0<α<1)

m = The number of periods ahead to be forecast

The underlying rationale of Brown's linear exponential smoothing is similar to that of linear moving averages: both the single and double smoothed values lag the actual data when a trend exists. The difference between the single and double smoothed values can be added to the single smoothed values and adjusted for trend.

In order to apply formula 2 and 3, values of S'_{t-1} and S''_{t-1} must be available. However, when t=1 no such values exist. Thus, these values will have to be specified at the outset of this method. This can be done by simply letting S'_{t-1} and S''_{t-1} be equal to X_t or by using some average of the first few values at the starting point.

This type of initialization problem exists in all exponential smoothing methods. If the smoothing parameter α is not close to zero, the influence of the initialization process rapidly becomes less significance as time goes by. However, if α is close to zero, the initialization process can play a significant role for many periods ahead [Makridakkis, 1983: 97].

Moving Average. The moving average is a forecasting technique where a constant number of data points can be specified at the outset and a mean computed for the most recent observations [Makridakis, 1983: 131-149]. As each new observation becomes available, a new mean can be computed by dropping the oldest value and including the newest one. Determining the appropriate length of a moving average is an important task. As a rule, a larger numbers of terms in the moving average increase the likelihood that randomness will be eliminated. That argues for using as long a length as possible. However, the longer the length of the moving average, the more terms are lost in the process of averaging, since N data values are required for an N-term average. According with Hanke and Reitsch [Dussault, 1994: 5] the moving average model performs best with stationary data; however, it does not handle trend or seasonality very well. Equation 1 provides the formula for the moving average forecasting technique.

$$F_{t+1} = (A_t + A_{t-1} + A_{t-2} + \ldots + A_{t-N-1}) / N \qquad (7)$$

where

A_t = Actual datum in quarter t

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

N = Number of terms in the moving average

Multiple Linear Regression. Once a linear relationship is established, knowledge of an independent variable can be used to forecast a dependent variable [Makridakis, 1983:189]. The method used to determine the regression equation in accordance with Hanke and Reitsch is the method of least squares [Dussault, 1994: 7]. Although the model is very responsive to any type of trend pattern, one disadvantage with linear regression is that it is complex and not easily understood by the user. In multiple regression there is one variable to be predicted, but there are two or more explanatory variables [Makridakis, 1998:241]. The general form of multiple regression is illustrated in equation 8.

$$Y = b_0 + b_1 X_1 + b_2 X_2 + \ldots + b_k X_k + e \qquad (8)$$

where

Y = Forecast value or dependent variable.

$b_0, b_1, b_2, \ldots, b_k$ = Linear regression coefficients.

$X_1, X_2, \ldots, X_k$ = Independent variable.

e_I = Is an estimate error term.

The practical application of this model requires the user to examine the following assumptions [Makridakis, 1998: 260]:

- The form of relationship between the forecast variable and the explanatory variable.
- The independence of residuals is also related to the validity of the F- and t-test, R^2, and confidence intervals.
- The regression model assumes that the residuals have the same variance, or homoscedasticity, throughout.
- Many regression models assume a normal distribution for the error term.

Autoregressive Model. It is still a regression equation, but differs from equation No. 8 in that the right-hand side variables are simply time-lagged values of the forecast variable [Makridakis, 1983: 356-359]. The general form of the equation for the autoregression model is illustrated in equation 9.

$$Y_t = b_0 + b_1 X_{t-1} + b_2 X_{t-2} + \ldots + b_k X_{t-k} + e \qquad (9)$$

where

Y_t = Forecast value or dependent variable.

$b_0, b_1, b_2, \ldots, b_k$ = Linear regression coefficients.

X_{t-k} = Time-lagged values of the actual demand values

e_I = Is an estimate error term.

In autoregression the basic assumption of independence of the error (residuals) terms can easily be violated, since the explanatory variable usually have a built-in independence relationship.

Comparison and Selection of Forecasting Methods

We now turn to factors that managers must consider in selecting a method for time series forecasting. Given the wide choice of alternative forecasting methods available (as presented in Table 3), it is useful to have a criteria that can be used to compare and select among competing methodologies [Makridakis, 1983: 761].

Conceptually, criteria for selecting and comparing forecasting methods can be organized in several ways:

- The accuracy of the forecast.
- The pattern of the data to be forecasted.
- The type of series.
- The time horizon to be covered in forecasting.
- The cost of applying alternative methodologies.
- The ease of application in organization situations.

A common approach is to prioritize criteria according to their order of importance. In practice (as might be expected), accuracy is given top priority, followed by the pattern of data, the time horizon and the type of series [Makridakis, 1983: 760-762]. The other two criteria, the cost and the ease of application are of minor influence [Silver, 1997: 76].

The Accuracy of Forecasting Methods

A variety of measures enable the forecaster to study the accuracy of the forecast; however, there is no a single universally accepted measure of accuracy. For the purpose of this research the following measures will be discussed:

Forecast errors. Forecasts usually contain errors. Errors can be classified as either bias errors or random errors [Krajewsky, 1996: 480]. Bias errors are the result of consistent mistakes; the forecast is consistently too low, or too high. These errors often are the result of neglecting or not accurately estimating components of demand such as a trend, seasonal, or cyclical movements.

The random error results from unpredictable factors that cause the forecast to deviate from the actual demand. The goal in forecasting is to try to minimize the effects of both bias and random errors by selecting appropriate forecasting models [Makridakis, 1983: 44].

The easiest form to measure the forecast error is simple the difference between the forecast and actual demand for a given period. If D_i is the actual datum for period i and F_i is the forecast for the same period [Makridakis, 1983: 44], then the error is defined as

$$E_i = D_i - F_i \tag{10}$$

The cumulative sum of forecast errors (CFE) measures the total forecast error. The mathematical formula is equation 11.

$$CFE = \sum E_i \tag{11}$$

Using this measure of accuracy it is possible that large positive errors could be offset by large negative errors in the CFE [Krajewsky, 1996: 480]. Nonetheless, CFE is useful in assessing bias in a forecast. For example, if the forecast is always predicting a lower value than actual demand, the value of CFE will become larger and larger. The increasingly large error indicates that perhaps during the forecasting calculations a time series component was omitted.

Other useful measures of the dispersion of the forecasting errors are the Mean Error (ME), Mean Squared Error (MSE), Standard Deviation of Errors (SDE) and Mean Absolute Deviation (MAD) [Makridakis, 1996: 481]. These tools are represented in equation 12 to 14 respectively.

$$ME = \frac{1}{N}\sum E_i \tag{12}$$

$$MSE = \frac{\sum E_i^2}{N} \tag{12a}$$

$$SDE = \sqrt{\sum E_i^2 \Big/ N-1} \tag{13}$$

$$MAD = \frac{\sum |E_i|}{N} \tag{14}$$

If MSE, SDE, or MAD is small, the forecast is typically close to actual demand; a larger value indicates the possibility of large forecast errors. The differences between the measures depend on the way they emphasize the errors. Large errors receive more weight in MSE or in SDE because the errors are squared. The effect of the mean error (ME) to the accuracy tends to be small since positive and negative errors tend to offset one another. In fact, the ME will only report you if there is a systematic under- or over-forecasting, called the forecast bias. It does not give much indication as to the size of the typical errors [Makridakis, 1997: 43]. The mean absolute deviation (MAD) is the mean of the absolute values of the forecast errors over a series of forecasts, without regard to whether the error was an overestimate or an underestimate. It is useful for assessing the magnitude of the deviation from the actual data [Makridakis, 1997: 43]. A similar idea is behind the definition of the mean squared errors. The MSE has the advantage of assessing the deviation from the actual data for large errors, since they are squared [Arostegui, 1998].

Another measure is the Mean Absolute Percent Error (MAPE) [Krajewski, 1996: 481]. This MAPE relates the forecast error to the level of demand and is useful for putting forecast performance in the proper perspective. Equations 15 and 16 represent the mathematical formula and the result is expressed as a percentage.

$$PE_i = (\frac{A_i - F_i}{A_i})(100) \qquad (15)$$

$$MAPE = \sum_{I=1}^{N} PE_i / n \qquad (16)$$

where

A_i = Actual demand value

F_i = Forecast value

N = Number of periods to be forecasted

Sometimes, for different items, the true quarterly demand is zero. If the true demand is zero, then the MAPE becomes undefined. For this reason, if the true demand is zero, the observation for this period should be ignored [Sherbrooke, 1987: 5].

A tracking signal is a measure that indicates whether a method of forecasting is accurately predicting changes in actual demand [Makridakis, 1996: 482]. The tracking signal measures the number of MADs represented by the cumulative sum of forecast errors, the CFE. The CFE tends to be 0 when an accurate forecasting system is being used. The tracking formula is represented by equation 17.

$$TrackingSignal = \frac{CFE}{MAD} \tag{17}$$

A statistical control chart is useful to determine whether any action needs to be taken to improve the forecasting model based on the tracking signal results. When the underlying characteristics of demand change but the forecasting model does not, the tracking signal eventually goes out of control. Choosing the limits for the tracking signal involves a tradeoff between the cost of poor forecast and the cost of checking for a problem when none exists.

The Pattern of the Data To Be Forecasted

The pattern of data is important because different methods perform better with only certain kinds of data patterns. There are, of course, methods that can cope with a variety of patterns, but these are usually more difficult to apply.

A data series can be described as consisting of two elements- the underlying pattern and randomness. The underlying pattern distinguishes four types: horizontal (or stationary), seasonal, cyclical and trend [Makridakis, 1983: 10, 777]. These patterns are represented in Figure 1.

1. A horizontal pattern exists when the data fluctuate around a constant mean. Such a series is "stationary" in its mean. A product whose sales do not increases or decrease over time would be of this type. Similarly, a quality

control situation involving sampling from a continuous production process that theoretically does not change would also be of this type [Makridakis, 1983: 10].

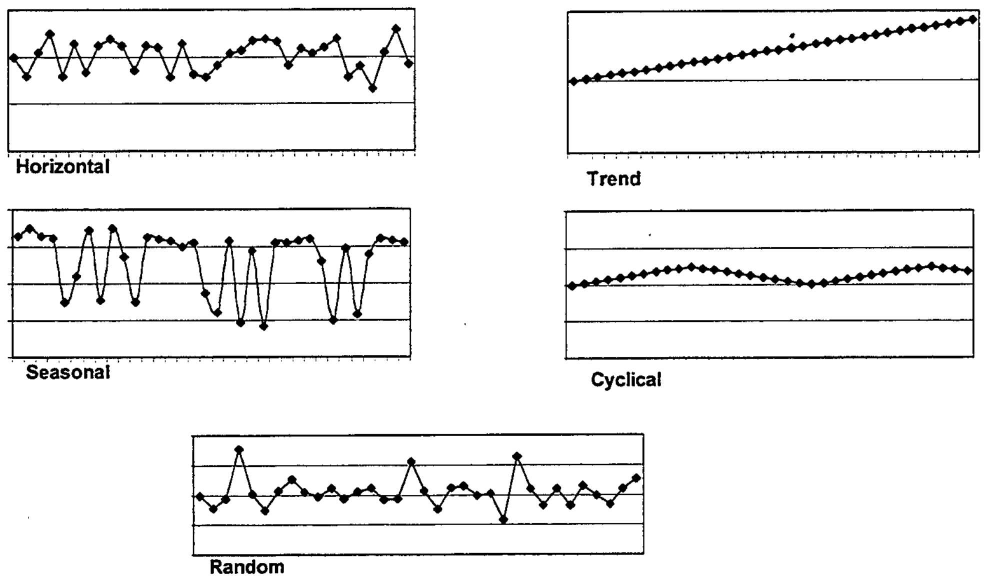


Figure 1. Time Series Component (Adapted from Neter, 1978: 612)

2. A trend describes the long-term factors whose effects might be the growth or decline in the time series over an extended period of time. Generally, these factors are population growth, price inflation, technological improvements, and productivity increases [Neter, 1978:611-612]. In an Air Force environment, an increase or decrease in operational activities could explain the trend component. A major application of trend analysis is found in long-term forecasting.

3. A seasonal component describes effects that occur regularly over a period of a year, quarter, month, week, or day [Neter, 1978: 613-614]. This component

tends to recur fairly systematic. Consequently, the pattern of movement in the seasonal component tends to be more regular than the cyclical pattern and therefore is more predictable. Seasonal movements can be taken into account in evaluating past and current activity, and so that they can be incorporated into forecasts of future activity.

4. A cyclical pattern exists when the data are influenced by longer-term fluctuations such as those associated with business cycles [Makridakis, 1983: 10]. The sales of products such as automobiles, steel, and major appliances exhibit this type of pattern. The major distinction between a seasonal and a cyclical pattern is that the seasonal exhibits a constant length and recurs on a regular periodic basis, while the latter varies in length and magnitude.

5. The random component [Neter, 1978: 614] describes residual movements that remain after the other components have been taken into account. Random movements reflect effects of unique and nonrecurring factors, such as strikes, unusual weather conditions, and international crises.

Knowledge of the type of patterns included in a data series can be very useful in selecting the most appropriate forecasting method. For example, the mean and the simple smoothing techniques can deal only with stationary (horizontal) patterns in the data, while linear or higher forms of smoothing (quadratics, cubic, etc.) can deal with linear or higher forms of patterns in the data. Other methods like Winters' exponential smoothing can deal with both trend and seasonal elements of a pattern. On the other hand, the single equation regression can deal with almost any pattern that can be transformed into a linear relationship. In regression, the ability to handle different patterns depends largely on the user's ability to specify the most appropriate regression model [Makridakis, 1983: 777].

The Time Horizon

One of the reasons the time horizon is particularly important in selecting a forecasting method in a given situation is that the relative importance of different patterns changes as the time horizon of planning changes [Makridakis, 1983: 778].

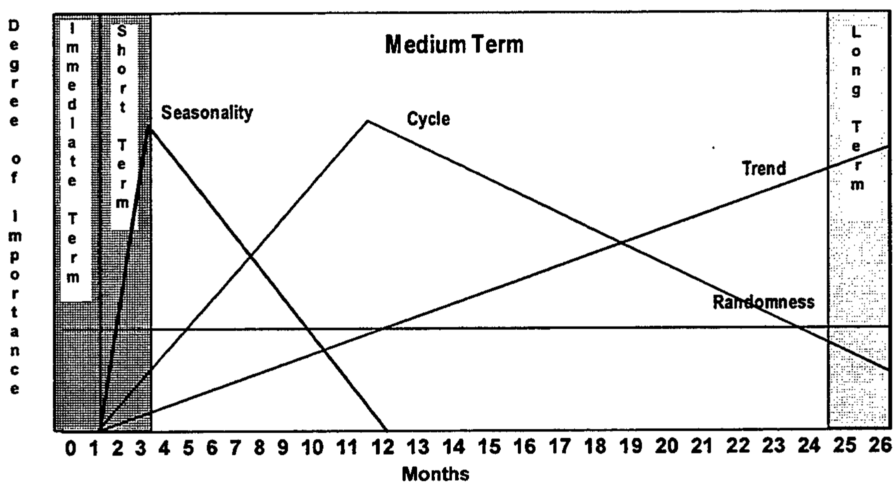


Figure 2. Relative Importance of Data Pattern for Different Time Horizons

As seen in Figure 2, in the very immediate term the randomness element is usually the most important. As the time horizons increase to two or three months, the seasonal pattern generally becomes dominant. Then, in the medium term, the cyclical component becomes more important, and finally in the long term, the trend element dominates [Makridakis, 1983: 778].

In general, quantitative methods can be applied for all time horizons as long as patterns do not change. Smoothing methods are usually best for immediate or short term and decomposition and autoregression methods are usually better for short to medium term. Regression techniques tend to be best suited for medium-to long-term usage. Furthermore, it is important to understand that as the time horizon of forecasting increases the chances of a change in established patterns or relationships increase too.

The Type of Time Series

Forecast error measures provide important information for choosing the best forecasting method for a demand item. These errors also guide managers in selecting the best values for the parameters needed for the method: n for the moving average method, the weights for the weighted moving average, and α for the exponential smoothing method. The criteria for choosing the parameters include: statistical criteria, meeting managerial expectations, and minimizing the forecast error last period. The first criteria relates to statistical measures based on historical performance, the second reflects expectations of the future, and the third is a way to use whatever method seems to be working best at the time a forecast must be made.

Using statistical criteria. Ideally, we would like to have forecasts with no bias and no MAD. As this is impossible, we must deal with tradeoff between bias and MAD. Normally, preference is given to lower values of MAD. However, in some cases where the values of MAD are not that different, the measures of bias are very different. A positive value for CFE indicates that, on balance the forecast has been too low [Krajeswski, 1996: 484-485].

These considerations are involved in choosing the α for exponential smoothing. For different values of α, the differences in MAD are slight, but the differences in bias can be considerable. Larger α values seems to result in less bias than do smaller values.

It is important to note that in the selection of the parameters, when a significant weight was given to the most recent levels of demand and less weight to earlier levels, a trend or seasonal component of demand may be present in the time series. However, to further reduce bias and/or MAD, methods that include trend or seasonal influence should be explored. It is also important to keep using a tracking signal to monitor the performance of the forecasting in the future [Krajeswski, 1996: 484-485].

Using Managerial Expectations. Managers can use to general guidelines in choosing the parameters that best fit their needs. First, to emphasize historical experience because of more stable demand patterns use lower α values, for exponential smoothing, or larger n values, for moving average. Second, for projections of more dynamic demand patterns, use higher α values or smaller n values. When the historical component of demand are changing, recent history should be emphasized [Krajeswski, 1996: 484-485].

Aircraft Spare Parts Characteristics

The central problem in logistics is to get the right item to the right place at the right time without incurring extra cost. To accomplish this it is necessary to understand the characteristics of the demand that is being studied.

There are two types of aircraft spare parts -- consumable spare parts and repairable spare parts [Christensen, 1994: 1]. Consumable spare parts are those items which are expended, consumed or used up beyond recovery during the use for which they were designed. Repairable spare parts are those items that may be repaired or reconditioned and returned to a serviceable condition for reuse.

According to Christensen [1995: 2] ninety-five percent of all the money spent on supplies stocked in a typical base supply organization is spent on repair cycle assets. In the US Air Force, this equates to an eight billion dollar investment. Repair cycle assets consists of only five percent of the total line items in the Air Force inventory. This is due to their high cost and repairability. Given this as well as the critical role that these parts play toward achieving the Air Force's mission, the quantity of these items to be stocked becomes an important issue.

In general, consumable items have a relatively low dollar value. However, a good understanding of the demand variability in those items and an effective and efficient economic order quantity (EOQ) can benefit the logistics system. Among the benefits could be a substantial monetary savings caused by a better tradeoff between ordering and holding costs. Additionally, an accurate EOQ model will decrease the probability of stockouts while increasing the operational availability [Blazer, 1985: 11-13]. Therefore, it is important to differentiate between consumable and repairable spare parts.

An understanding of the pattern of demand is essential for the design of an effective and economical logistics system. The demand pattern can be classified into two types: high and low demand [Brown, 1956:1]. High demand represents items that are issued frequently. Low demand represents items that are issued with low frequency.

According to Brown [1956:13], the vast majority of parts have very low demand, but the few parts that have high demand account for most of the units that are required. Brown suggested that these two typical patterns of demand, high and low, have important implications for the logistics system. This was because about half of the parts causing AOCP (aircraft out of commission for parts) had a very low demand during the previous year. In other words, the pattern of demand for low demand items is very difficult to determine, while that of the high demand the pattern is more predictable [Brown, 1956: 14]

There are two types of aircraft spare parts: specific and common. Specific parts represent items that have application to one weapon system. Common parts represent those items that have applications for two or more weapon systems. Eighty-five percent of the total repairable items' population is specific to weapon systems, while fifteen percent are the common parts [Dussault, 1995: 8].

When determining spare part quantities, one should consider system operational requirements. For instance, spares required to support prime equipment components which are critical to the success of a mission may be influenced by different factors: high cost, low cost, high demand, low demand; and so on. In any event, the factors may be handled differently [Blanchard, 1994:112].

Summary

This literature review provided background information to understand the importance of forecasting in enhancing the logistics planning function. The chapter also presented descriptions of the logistics environment at the Colombian Air Force, the data pattern components, the forecasting techniques most commonly used in the US Air Force, US Navy and the remanufacturing industry, and the characteristics of aircraft spare parts. Finally, the tools to measure the forecasting accuracy are presented.

Data can be decomposed into components known as trend, cycle, seasonality, and randomness. The most commonly used forecasting techniques used in the military environment are the moving average, exponential smoothing, double exponential smoothing, and linear regression.

Forecasts always include errors in its calculations. The errors are bias or random errors. The goal in forecasting is to minimize errors. The way to minimize errors is to use statistical tools to measure the forecasting accuracy and to choose the forecasting technique appropriated for the demand pattern.

Forecast errors guide managers in selecting the appropriate forecasting technique and the best values for the parameters needed for each particular method. The criteria to choose the parameters include statistical criteria, managerial expectations, and minimization of the forecast error. The next chapter discusses how the actual research was conducted. It also describes how the data were obtained and analyzed.

III. Methodology

Introduction

The purpose of this study is to provide an evaluation of different forecasting techniques in a convenience sample, and to develop a forecasting procedure to be applied later in the Colombian Air Force.

This chapter discusses the methodology used in the research process to answer the research questions identified in Chapter I. The research questions are reviewed and the hypotheses are identified. Then the general research design is explained. The analytical approach, population size, sample size, data collection, choice of factor and level, selection of the response variables, and limitations used to perform the study are also discussed. Finally, this chapter highlights the actual research plan.

Research Questions

To evaluate the different forecasting techniques and to address forecasting accuracy and robustness, the following research questions must be answered:

1. Can forecasting techniques improve the planning process of future requirements, aircraft spare parts, with the current information provided by the CAF logistics information system, EQUALS?
2. What forecasting technique is more appropriate for each demand pattern category?

Research Question No. 1

The main purpose of this research question is to evaluate if the forecasting techniques can improve the current planning process for spare parts requirements, observed from historical data, in terms of total relevant cost of the inventory. The ending inventories in each period under the current system versus the forecasting system will be compared. To answer the research question the following investigative questions are developed:

1. What are the starting inventories under the current management techniques versus a proposed forecasting system, from the actual data observed from historical demand?
2. What is the ordering policy under the current system observed from historical demand data?
3. What are the monthly ending inventories under the current system and the proposed forecasting system observed from historical demand data?
4. What would the cost difference be between the current system and the proposed forecasting system, in terms of net present value?

Research Question No. 2

The purpose of this research question is to determine how accurate the forecasts computed by each forecasting technique would be. To answer the research question, the following investigative questions are developed:

1. What is the forecasting error in terms of the mean error, cumulative forecasting error, mean absolute deviation, mean squared error, and mean absolute percentage error?
2. What are the differences between the different forecasting techniques in terms of the forecasting error?

Research Hypotheses

To answer the first research question, a hypothesis is developed which can be applied to each demand pattern type. The hypotheses to be tested are that forecasting methods can improve supply performance, and that forecasting techniques do not work equally well in all demand categories.

$H1_o$: No performance difference exists between forecasting methods and current demand management techniques.

$H1_a$: At least one forecasting method is different from current demand management techniques.

To answer the second research question, a factorial experiment will be conducted. A full factorial design of 3 factors with 2 levels each and 5 treatments is being used. The factors represent important demand patterns and the treatments represent the forecasting techniques. The hypotheses to be tested are:

$H2_o$: No performance differences between $F_1, F_2, \ldots F_n$ in all factor level combination.

$H2_a$: At least one treatment differs in at least one factor.

In order to determine the nature of the treatment effect, if any, on the response in a factorial experiment, it is necessary to break the treatment variability into four components. These components are: interaction between the three factors, main effect of factor 1, main effect of factor 2, and main effect of factor 3. The interaction component is used to test whether the factors combine to affect the response. The main effects are used to determine whether the factors affect the response. Therefore, depending upon the rejection of the null hypothesis, additional sets of hypotheses will be addressed later in this chapter.

Type of Research Design

A research represents the blueprint for the collection, measurement, and analysis of data. It is the plan and structure of investigation conceived to obtain answers to research questions. The plan is the overall scheme for the research, and the structure describes the relationships among the variables in the study [Emory 1996: 114].

The research may also be viewed from different perspectives such as the method of data collection, the design of the research, the purpose of the research, the topical scope and the environment. The next paragraphs will characterize this research effort along Emory and Cooper's dimensions [1996: 114-116].

The <u>Method of Data Collection</u> depends on whether the research is observational or follows the survey mode. An observational study refers to a study where the researcher collects data about a subject without interacting with it. In the survey mode, the researcher questions the subject(s) and collects their responses by personal or impersonal means. This research falls in the category of an observational research. The actual data, observed from historical demand data, is evaluated under different forecasting techniques to determine which technique is more appropriate for each demand category.

The Design of the Research depends on whether the researcher has control over the variables being studied. There are two types of research design: the experimental design and the ex post facto design. Experimental design is determined by the researcher to produce effects in the variables under study. With an ex post facto design, the researcher does not have control over the variables and can only report what has happened or what is happening. This thesis research deals with the experimental design because the researcher exerts control over the independent variables through the factors and treatments.

The Purpose of the Study depends on whether the research is descriptive or causal. The descriptive study is concerned with finding out who, what, where, when, or how much. It deals with a question or hypothesis being stipulated concerning the size, form, distribution or existence of a variable. A causal study is interesting with learning why or how one variable affects another. It tries to explain the relationship that can exist among variables. This research is causal because the researcher is manipulating a set of independent variables to determine the effect on the dependent variable, and it answers the following question: what forecasting techniques are more accurate in forecasting the aircraft spare part demand depending on the demand category?

The Topical Scope of the research depends on the breadth and depth of the study. The scope could be a case study or a statistical study. The case study place more emphasis on a full contextual analysis of fewer events or conditions and their interrelation. A statistical study attempt to capture a population's characteristics by making inferences from a sample's characteristics based on hypothesis to be tested quantitatively. This thesis research is a statistical study. It tries to determine which forecasting techniques are best to predict the different demand categories selected.

The Environment depends on whether the research is conducted in the field or in the laboratory. In the field refers to performing the research under actual environmental conditions. The laboratory refers to investigating the problem under tightly controlled conditions. This research tries to study the behavior of the aircraft spare parts demand under tightly controlled conditions; the forecasting methods and demand pattern factors.

In summary, the design of this thesis research is as follow: the method of data collection is observational, the design is experimental; the purpose of this study is causal; the topical scope is a statistical study; and the environment is the laboratory.

Experimental Design

An experiment can be defined as a test or series of tests in which purposeful changes are made to the input variables of a process or a system so that we may observe and identify the reasons for changes in the output responses [Montgomery, 1996: 1].

The experimental design refers to the number and arrangement of independent variable levels in a research project [Dane, 1990: 89]. Although all experimental designs involve manipulated independent variables and random assignments, different designs are more or less efficient for dealing with specific alternative explanations.

The design used for a particular experiment depends on the research hypothesis. The major factor in choosing a design is not its complexity, but the extent to which it provides internal validity. Internal validity refers to the extent to which the independent variable is the only systematic difference among the experimental groups. This internal validity allows you to conclude that the independent variable is the cause of the effects you measure with the independent variable.

The kinds of experimental design available for the researcher is as follows: The Basic Design, the Basic Pretest Design, the Solomon Four-Group Design, the Factorial Design, and the Repeated Measures Design [Dane, 1990: 88]. The next paragraphs will characterize the experimental design effort along Dane dimensions [1990:90-96].

The Basic Design is the simplest design that still qualifies as a true experiment. In the basic design the participants are randomly assigned to one or two different levels of independent variable, and the dependent variable is measured only once.

The Basic Pretest Design involves adding a pretest measure to the basic design. The obvious reason for adding a pretest measure is to examine how much the independent variable causes participants to change.

The Solomon Four-Group Design is used when there is a possibility of testing-treatment interaction. However, the interaction only allows two levels of a single independent variable. The loss of efficiency is related to the need to test for the testing-treatment interaction. In general, the more you need to know, the more groups will be required.

The Factorial Design accounts for the inclusion of more than one independent variable in the experiment. The advantage of a factorial design is that interactions between independent variables can be tested. An interaction occurs when the effect of one variable depends on which level of another variable is present.

The Repeated Measures Design is a specific factorial design in which the same participants are exposed to more than one level of an independent variable. Repeated measures design is also called "within subject" designs because the independent variable is manipulated within the same subject instead of between or across different subjects.

Therefore, this research can be classified as a factorial experiment because it is including more than one independent variable in the hypothesis testing. As it will be explained later in detail, this research includes five different forecasting techniques, and three factors, each with two levels.

Research Approach

Four analytical phases were used to evaluate the logistics requirements for different forecasting techniques with the data provided for the experiment.

The first phase identified the characteristics of the aircraft spare parts demand patterns. This allowed the selection of the appropriate forecasting techniques to be used during the study. This phase includes the following specific requirements:

1. Description of the sample of aircraft parts.
2. Description of the types of data used during different phases of the experiment.

3. Relevant factors of the sample, aircraft spare parts, to be studied.
4. Select the aircraft spare parts to be used in the experiment based on the previous categorization.
5. Select the data time increment used for demand data.
6. Determine the forecasting techniques to be used during the experiment.

The second phase, evaluating the forecasting techniques, consisted of measuring the performance of the forecasting techniques using the actual data, observed from historical demand data, to answer the research questions. This phase included the following specific requirements:

1. Define the parameters for each forecasting method that maximize the accuracy in terms of forecasting error.
2. Perform the forecasting using actual data, observed from historical demand data, from 1996 and previous parameters to predict the quantities required for 1997.
3. Perform an Analysis of Variance to determine if performance differences exist between the 5 treatments across the 8 levels of the three factors.
4. Perform non-parametric test on a set of additional accuracy measures if the parametric ANOVA fails.

The third phase consisted of testing and validating a simulation model to perform the experiment, if previous phase fails to detect any difference. This phase included the following specific requirements:

1. Model conceptualization to define the object of interest and the type of simulation to be used.

2. Identify the time series component of the data, and remove the trend-cycle and seasonal component.
3. Determine the underlying statistical distribution that best represent the irregular component of the demand pattern.
4. Generate 24 random data points using the underlying distribution that represents the irregular component of the demand pattern.
5. Obtain 24 simulated demand data including seasonal component and the trend-cycle to the previous 24 random data points.
6. Perform a paired t-test to determine if the simulated data belongs to the same population of the actual demand data.
7. Determine the forecasting parameters for to be used during the simulation based on the actual 24 demand data points, observed from historical demand data.
8. Production runs and analysis to estimate measures of performance for the system design that are being simulated.

The fourth phase included the use of the simulation model to generate additional demand data, if previous production runs required more replications. This phase include the following specific requirements:

1. Use simulated demand data to determine the number of replications required to obtain enough confidence to analyze the results.
2. Analyze the results in terms of the forecasting errors, using the mean error, the mean absolute deviation, and the mean squared errors.

During the execution of the steps included in each of the four phases, the respective analytical approach will be discussed in detail only for one item, and calculations for the rest of the items will be in the list of appendixes. The implementation will follow each phase systematically.

Phase 1- Design The Experiment

Specific actions taken in phases 1 to 3 of the research will now be presented. Specific results of phase 4 are presented in Chapter 4. Results presented will only include a single example, with full results available in the appendices.

Description of the Sample

The sample to be used in the experiment is a convenience sample because the CAF data was unavailable. This sample was obtained from a Colombian commercial airline called "Aires". Taking into consideration the fact that the quality of the maintenance process between this company and the CAF are not equal, they still have some similarities between each other that make them comparable. There are several important similarities which included the basic aeronautical education for pilots and mechanics, the environment in which the flight operations are conducted, the maintenance procedures, and the multiple manufacturer characteristics. With regard to their basic aeronautical education, the majority of pilots and mechanics had served in the CAF. Regarding the environment, the flight operations are affected in similar fashions in both organizations because they use the same airports and are affected by the same weather or environmental conditions. Relating to the maintenance procedures, this company and the CAF operate in some instances the same type of aircraft (Bandeirante). In other cases, they use the same manufacturer (Fokker), and still in other cases, the same aircraft size (Dash8), which implies similar maintenance procedures. Additionally, failures occur due to the natural deterioration of the materials rather than improper maintenance procedures. Finally, the three aircraft's types being analyzed are built in different countries, which accounts for the CAF problems caused by multiple manufacturers.

These similarities between the two organizations suggest that they are comparable; but the results of studying Aires aircraft might not be directly applicable to CAF because the process of collecting the information in both organizations is different. However, this collection of information does not affect the process developed to use the forecasting techniques. Instead, it must be validated with CAF data.

The Aires data include the following information for each item: part number, tail number designation, requisition control number, issue date, unit cost, and quantity issued from January 1, 1996, to December 31, 1997. During the period where the sample was collected, the company flew 24,567 hours and 48,089 cycles. The sample comprises 5 Dash-8, one Fokker F-27 and two Bandeirante. The Dash 8 is manufactured in Canada, the Fokker F-27 in Holland, and the Bandeirante in Brazil. The following table illustrates the general characteristics of the sample being studied:

Table 3. General Characteristics of the Sample Being Studied

Type of Aircraft Spare Part	Total Number of Parts	Total Number of Issues	Cost (US$)
Consumable	2529	122,952	1,754,543.99
Repairable	583	2,781	10,748,106.07

Types of Data

Another important issue that warrants explanation involves the different types of data used during the study. This is of significance because depending on the phase the data may change. In order to provide the explanation, the following types of data were used:

- Actual data observed from historical demand data. This data corresponds to the true demand of spare parts required by the mechanics to be installed on the aircraft.
- Actual data observed from simulated demand data. This data corresponds to new demand of spare parts created from the underlying statistical distribution.
- Forecasted data based on historical demand data. The forecasted data was created with different forecasting techniques which used actual data. That data was obtained from historical demand data.
- Forecasted data based on simulated data. The forecasted data was created with different forecasting techniques which used actual data. That data was obtained from simulated demand data.

Relevant Factors of Aircraft Spare Parts Demands

Several factors are important in selecting representative spare parts to be forecasted. Three factors of interest (as introduced in Chapter 2) will be studied. In general, the demand patterns are a function of the repairability (consumable and repairable), uniqueness (common or specific), and demandability (high and low) [Dussault, 1995: 9].

The repairability is important because repairable and consumable items have an important impact on inventory decisions. The demandability is important because low demand items are more difficult to predict than high demand items. The uniqueness is of significance because it is in the interest of the researcher to know if the uses of multiple manufacturers affect the demand rate between aircraft parts.

Selection of Representative Aircraft Spare Parts

The next step was to select the representative aircraft spare parts to be used in the experiment. A single part was selected to represent the class of parts in each factor and level combination. Differences in demand rates within the consumable and repairable classes, lead to demand level boundaries as follows:

- High demand consumable items greater or equal to 150 issues in 24 months.
- High demand repairable items greater or equal to 50 issues in 24 months.
- Low demand consumable and repairable items greater or equal to 15 issues and less than 30 issues in 24 months.

It is important to clarify that the boundaries selected for high demand were different across consumable and repairable because in normal conditions, consumable consumption is higher than for repairable items. On the other hand, the lower boundary selected for low demand consumable and repairable items was influenced by the minimum size of an acceptable demand during the two years.

Another issue to be resolved was the definition of commonality between aircraft spare parts. In order to be more confident about the existence of commonality, the rule applied was that it had to be used in all three aircraft types studied. It means that a common item must be used in the Fokker F-27, the Bandeirante, and the Dash 8. A specific or unique item would be used in only one type of aircraft. Based on the previous decisions and considerations, our original candidate parts are classified in Table 4.

Table 4. Total Number of Parts Useful for Selection

Demandability		Reparability		Uniqueness	
High	Low	Consumable	Repairable	Specific	Common
37	220	209	48	189	68

With the data available for the experiment, the following step was to select one part number to represent each of the categories selected for the experiment. The selection was based on part numbers that present a typical demand pattern, and with the assumption that the information contained in the demand for each part number is accurate. The part numbers selected are presented in Table 5.

Table 5. Part Number Selected for Conducting the Experiment

Reparability	Demandability	Uniqueness	Name	Part Number	Applicability
Consumable	Low	Common	Light	307	Dash8, F27, Bandeirante
	Low	Specific	Battery Ni-Cad	61-0478-9	Dash 8
	High	Common	Pin Cotter	MS24665-134	Dash8, F27, Bandeirante
	High	Specific	Bulb-Lamp	F1815/WW/RS	Dash 8
Repairable	High	Common	Oxygen Bottle	ZP650-SC-M-B-3	Dash8, F27, Bandeirante
	High	Specific	Brake-Assy	2-1517	Dash 8
	Low	Common	Receiver ADF	622-2362-001	Dash8, F27, Bandeirante
	Low	Specific	Inverter	DH1030-24-600CS	Dash 8

Time Increment

The time horizon selected for the forecasting was monthly. The original demand data was daily, and was converted to monthly data. The forecasting methods were then used to forecast in monthly quantities. This decision was taken to account for the monthly seasonal and trend–cycle component, and to match the replenishment policy used for the company whose this demand data belongs to.

The monthly seasonal and trend-cycle components are of the interest to the researcher because the proposed study is designed to cover a problem located at the Colombian Air Force headquarters level. At this level of management the interest is to track the aircraft spare parts requirements as a big picture, and a monthly pattern is considered a reasonable frequency for the length of the demand data obtained.

The replenishment policy used for the company that provided the demand data is based on historical purchases and consumption rather than any of the forecasting techniques mentioned in the literature review. In other words, the replenishments are done with the same periodicity and in the same quantity every year. The information provided by the company related to the replenishment policy, quantities purchased in 1997, were used for the comparison of the total relevant cost of the inventory between the two systems in the year in mention.

Forecasting Techniques to Be Used

In practice, several factors were important in selecting the forecasting method. In order of importance the factors driven the selection were the accuracy in predicting actual demand data, the inherent adaptability of the forecasting method to changes in the data, and previous experiences with the methods in similar environments. Based on these conditions, the forecasting methods to be used were as follows:

- Single exponential smoothing, or forecasting method No. 1
- Double exponential smoothing –Brown Method, or forecasting method No. 2
- Moving Average, or forecasting method No. 3
- Autoregression, or forecasting method No. 4
- Multiple linear regression, or forecasting technique No. 5

Phase 2- Forecasting Techniques Performance with Actual Data

The first step in preparing the data to perform the forecasting technique in each individual demand category was to convert it to monthly demand data [see Appendix B]. The number of days representing the monthly data are the same as the annual calendar for the year in study (i. e. February 1996 includes the sum of the monthly demand data between the 1st to the 29th days respectively. February 1997 includes the sum of the monthly demand data between the day 1st to the day 28th, and so on).

Calculation of the Parameters

The next step was to find the parameters for each forecasting method that produces the least forecasting error. The actual data observed from historical demand data from 1996 was used to predict the demand for 1997. Specific parameters were selected for each part and each forecasting method based on the one that produced the smaller MAD. In those cases where the MAD was equal across other parameters, the CFE closest to zero was used [Krajewsky, 1996: 484-485]. The selection of the parameters was calculated for all the forecasting techniques across the eight levels of the three factors.

Selection of parameters consisted in calculating the value of α, for single and double exponential smoothing constant, and the number of periods to be averaged for moving average. In the case of the regression analysis, the equation coefficients that best predicted quantities for 1997 depended on cycles, hours, and periods. For the autoregression model, the regression equation that best predicted the quantities for 1997 depended on lag 1, 2 and 3 models.

<u>Single Exponential Smoothing</u>. The higher the value of α, the greater is the weight placed on the most recent demand level. On the other hand, the lower the value of α, the greater is the weight given to demand history. Using equation No. 1 in an excel spreadsheet, the parameter α was calculated by means of analyzing the forecasting response (MAD or CFE) with different values between 0 and 1. The α parameter, which produced the least MAD, or CFE when it applies, was selected [Krajeswski, 1996: 484-485].

Double Exponential Smoothing. The selection of the parameter is performed in a similar way as in the single exponential smoothing. If the α value was close to zero meant that the decomposition of the time series, seasonal and trend-cycle, can play a significant role for many time periods ahead data [Makridakis, 1983: 97]. However, for the purpose of this phase the decomposition method was omitted.

Moving Average. Under this situation the maximum months that can be averaged to obtain the best fit parameter did not exceed 11 months because it only had 12 available periods. To figure out the best moving average the MAD and CFE were calculated trying 2, 3, 4, 5…11 periods; then, the one with the smaller error was selected.

Autoregression. The procedure used with this forecasting method to calculate the parameters was a little bit different because the additional calculations required to find the regression coefficients. First, this autoregression model was built with lags one, two and three. Then, for each possible equation a set of parameters was calculated. After that, this coefficients were used to predict the quantities for 1997 and the one that produced the smaller MAD, or CFE, was selected.

The multiple regression procedure to find the parameters that best predict the actual demand was calculated using the statistics software SPSS 8. 0. To help sort out the relevant explanatory variable (one, two or three lags) a stepwise backward regression was used.

Backward regression is a variable selection procedure in which all variables are entered into the equation and then sequentially removed. The variable with the smallest partial correlation with the dependent variable is considered first for removal. If it meets the criterion for elimination, it is removed. After the first variable is removed, the variable remaining in the equation with the smallest partial correlation is considered next. The procedure stops when there are no variables in the equation that satisfy the removal criteria.

However, for the purpose of this test, the three regression equations obtained from the first twelve data points, based on lag 1, 2 and 3, were used to reproduce the forecasting value for the following twelve months [see Table 6]. Once the predicted values were obtained, they were compared against the actual quantities to choose the one which produced the best MAD result.

Table 6. Autoregression Model Coefficients Using Historical Demand Data (1996)

Parameters Used in the Autoregression Model						
Reparability	**Demand**	**Uniqueness**	β_0	$\beta\tau_{-1}$	$\beta\tau_{-2}$	$\beta\tau_{-3}$
Consumable	Low	Specific	11.353	-0.698	0.109	0.495
	Low	Common	4.781	0.368		
	High	Specific	6.742		0.825	
	High	Common	167.562			0.306
Repairable	High	Common	2.165	0.869		
	High	Specific	3.461		-0.657	
	Low	Common	1.438	-0.582	0.0213	0.293
	Low	Specific	0.946		-0.189	

Linear Regression. The causal variables used to explain the dependent variable demand were the month or period, the flying hours, and the cycles. The best model with its respective coefficients was calculated [see Table 7] using the same backward stepwise regression presented in previous forecasting method.

Table 7. Regression Model Coefficients Using Historical Demand Data (1996)

Parameters Used in the Regression Model						
Reparability	Demand	Uniqueness	β_0	Month	Hours	Cycles
Consumable	Low	Specific	1.53	0.79		
	Low	Common	7.227	0.0804		
	High	Specific	54.719	3.043	-0.0334	
	High	Common	146.879	11.839		
Repairable	High	Common	-1.333	1.038		
	High	Specific	2.247	0.0781	0.00833	-0.00048
	Low	Common	2.669			-0.00073
	Low	Specific	1.318E-16			0.115

The parameters selected to perform the forecasting analysis using the actual data, observed from historical demand data corresponding to 1996 in all 40 possible combinations of treatments, factors and levels are showed in Table 8.

Table 8. Forecasted Demand Parameters Used Historical Demand Data (1996)

Parameters Used for Forecasting							
Reparability	Demand	Uniqueness	F1	F2	F3	F4	F5
Consumable	Low	Specific	0.6	0.1	5	lag 1,2,3	month
	Low	Common	0.4	0.3	5	lag1	month
	High	Specific	0.3	0.8	5	lag 2	month-hours
	High	Common	0.4	0.7	5	lag 3	month
Repairable	High	Common	0.1	0.4	4	lag 1	month
	High	Specific	0.6	0.2	8	lag 2	month-hours-cycles
	Low	Common	0.1	0.5	9	lag 1,2,3	cycles
	Low	Specific	0.3	0.3	8	lag 2	cycles

Analyzing the results the α value in single exponential smoothing told us that a small value of α is given a greater weight to demand history (repairable- low demand-common or specific). A higher value of α (consumable-low-specific and repairable-high-specific) told us that a greater weight is assigned on the most recent demand level.

In the case of double exponential smoothing the α values resulted in similar conclusions as single exponential. In addition, a α value of 0.1 (consumable-low-specific) told us that a seasonal or trend-cycle phenomena was present.

Looking at the moving average parameters, the consumable items used the same value of 5 previous periods indicating that these historical data is important. For the repairable case a moving average of 9 periods worked well most of the time.

Analyzing the lags used for autoregression, the parameters obtained with one lag are giving a greater weight to demand history; while a parameter of lag three, is giving greater weight to recent demand level [Makridakis, 1983: 357].

Finally, the linear regression parameters indicate which one of the three explanatory variables (month, hour or cycles) were most useful in predicting the dependent variable (demand for 1997).

Performing The Forecasting Techniques

Once the parameters have been established, the next step was to use the forecasting method for each of the 40 possible combinations of treatments, factors and levels. The forecasting calculation was performed by mean of an Excel spreadsheet using the formulas provided in Chapter 2.

For the purposes of this section the forecasting calculation for one item is displayed [see Table 9]. Complete information for the remaining parts are included in Appendix C " Forecasting Calculations for 1997 Using Historical Demand Data".

Table 9. Single Exponential Smoothing Calculations on P/N 61-0478-9

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty1	CONS-L-S	61-04789	Battery Ni-Cad	alpha=0.6	Exponential	$49.13
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	19	4	15	221.63	78.35
Feb	2	12	13	-1	1.09	8.71
Mar	3	0	12	-12	154.21	#DIV/0!
Apr	4	14	5	9	81.59	64.52
May	5	10	10	0	0.15	3.87
Jun	6	22	10	12	140.31	53.84
Jul	7	12	17	-5	27.69	43.85
Aug	8	16	14	2	3.59	11.85
Sep	9	0	15	-15	232.32	#DIV/0!
Oct	10	25	6	19	357.33	75.61
Nov	11	16	17	-1	2.07	8.99
Dec	12	1	17	-16	242.60	1557.55
Sums		**147**	**142**	**5**	**1464.57**	**#DIV/0!**
Measures of Accuracy						
CFE	ME	MAD	MSE	SE	MAPE	
5	0.43	9	122.05	11.54	#DIV/0!	

As it can be seen in Table 9, the MAPE showed an indefinite value because there is zero (0) demand in March and September. If the true demand is zero, then the MAPE becomes undefined. For this reason, if the true demand is zero the MAPE observation is not possible and should be ignored [Sherbrooke, 1987: 5]. The next step was to summarize the individual results of the measures of forecasting error and they are presented in Table 10.

Table 10. Measures of Forecasting Errors

FACTORS	ACCURACY	F1	F2	F3	F4	F5
Consumable Low demand Specific	CFE	5	-1	9	32	67
	ME	0.4	-0.1	0.8	2.7	5.6
	MAD	0.43	0.07	0.75	2.66	5.59
	MSE	122.05	82.42	79.61	80.57	105.71
Consumable Low demand Common	CFE	-19	4	-25	-55	-81
	ME	-1.6	0.3	-2.1	-4.6	-6.8
	MAD	1.55	0.36	2.12	4.55	6.75
	MSE	10.11	11.66	18.35	22.16	46.72
Consumable High demand Specific	CFE	-7	0	-1	-3	32
	ME	-0.6	0.0	-0.1	-0.3	2.7
	MAD	0.56	0.01	0.005	0.23	2.63
	MSE	65.83	1616.42	57.18	71.73	237.2
Consumable High demand Common	CFE	-3	-86	3	66	1139
	ME	-0.3	-7.2	0.3	5.5	94.9
	MAD	0.25	7.16	0.23	5.54	94.95
	MSE	1301.69	4798.73	1579.8	1635.56	15703.86
Repairable High demand Common	CFE	-17	-2	-34	-29	-36
	ME	-1.4	-0.2	-2.8	-2.4	-3.0
	MAD	1.41	0.18	2.8	2.42	3
	MSE	14.08	31.43	32.41	15.04	70.19
Repairable High demand Specific	CFE	4	0	6	9	7
	ME	0.3	0.0	0.5	0.8	0.6
	MAD	0.34	0.01	0.51	0.75	0.58
	MSE	3.05	18.08	2.76	3.21	3.26
Repairable Low demand Common	CFE	1	-2	-3	1	0
	ME	0.1	-0.2	-0.3	0.1	0.0
	MAD	0.07	0.13	0.22	0.11	0
	MSE	4.62	9.21	4.72	7.06	4.09
Repairable Low demand Specific	CFE	1	1	0	2	-2
	ME	0.08	0.08	0.0	0.2	-0.2
	MAD	0.05	0.05	0	0.18	0.16
	MSE	3.02	4.11	2.3	2.34	2.35

Analysis of Variance, ANOVA

Eight (8) aircraft parts were selected to participate in the experiment in order to determine the effects of repairability, demandability and uniqueness on the accuracy of the five different forecasting methods. For the initial analysis, a factorial procedure (General Linear Model) was performed. Factorial procedures are those involving more than one factor, as well as combinations of the factors. F tests can be conducted to determine whether treatment means differ, and, if so, whether the factors interact or independently affect the response mean [McClave, 1994: 908]. When the analysis of variance indicates that the average responses of treatment means differ, it is usually of interest to make comparisons between the individual treatment means. In this case a Bonferroni test was performed with an overall confidence level of 95%.

When performing the GLM factorial analysis, some assumptions [McClave, 1994: 532, 901] are necessary to assure the validity of the analysis. They are:

- For any given set of values $x_1, x_2 \ldots x_n$, the random error ε has a normal probability distribution with mean equal to 0 and variance equal to σ^2.
- The random errors are independent in a probabilistic sense.

Before the conclusions from the analysis of variance are adopted, the adequacy of the underlying model should be checked. The primary diagnostic tool is an analysis of the residuals. The residuals from the absolute value of forecast error are shown in Figure 3. The normal probability plot and dot diagram of these residuals reveals that the residuals are not normally distributed. Then, plotting the residuals versus the predicted values indicates that the variances of the results are not constant. Therefore, the assumptions necessary for the validity of this tests (normality and equal variances) are not being satisfied.

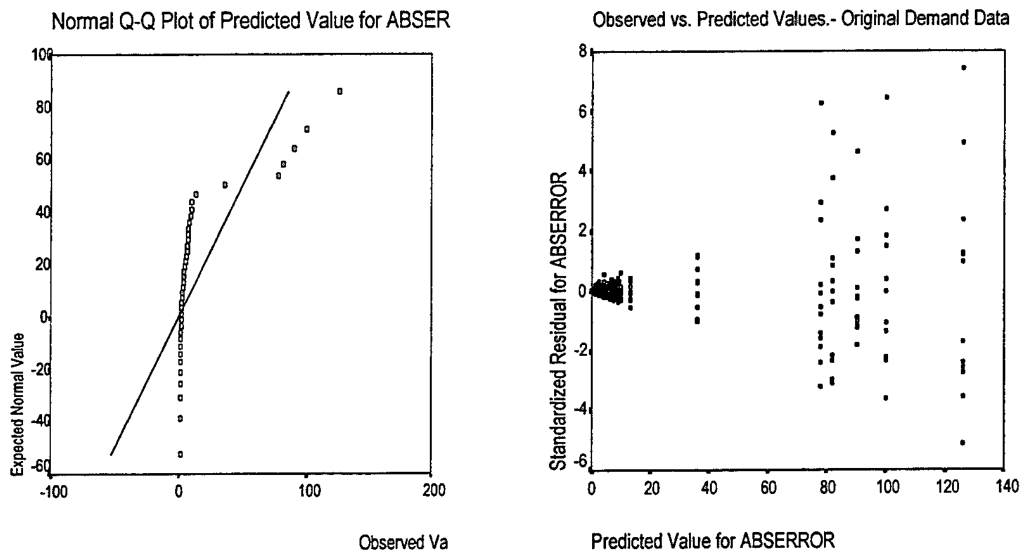


Figure 3. Analysis of Normality and Equal Variances

If these assumptions are not met, then the analysis of variance procedure is not an exact test of the hypothesis of no difference in treatment means. Consequently, it is usually unwise to rely on the analysis of variance until the assumptions have been validated [Montgomery: 1997: 79-80]. Even though the ANOVA assumptions were not met the ANOVA results are presented to gain a general understanding about the performance of the forecasting methods [Table 11].

The first test was:

H_o: No performance differences between treatments in $F_1, F_2, \ldots F_n$ for all factor level combination.

H_a: At least one factor and level combination differs from others.

Table 11. ANOVA Table Using Historical Demand Data

Tests of Between-Subjects Effects

Dependent Variable: ABSERROR **Source**	**Type III** **um of Squar**	**df**	**Mean** **Square**	**F**	**Sig.**
Corrected Model	460177.831	39	11799.432	21.199	0.0000
Intercept	129002.419	1	129002.419	231.766	0.0000
TREATMENT	**6166.154**	**4**	**1541.539**	**2.770**	**0.0270**
REPAIR	**93996.019**	**1**	**93996.019**	**168.873**	**0.0000**
DEMAND	**77140.052**	**1**	**77140.052**	**138.590**	**0.0000**
UNIQUE	**47740.352**	**1**	**47740.352**	**85.770**	**0.0000**
TREATMENT * REPAIR	4597.971	4	1149.493	2.065	0.0844
TREATMENT * DEMAND	6659.313	4	1664.828	2.991	0.0187
REPAIR * DEMAND	66481.669	1	66481.669	119.441	0.0000
TREATMENT * REPAIR * DEMAND	5390.946	4	1347.736	2.421	0.0477
TREATMENT * UNIQUE	542.596	4	135.649	0.244	0.9134
REPAIR * UNIQUE	40095.352	1	40095.352	72.035	0.0000
TREATMENT* REPAIR * UNIQUE	502.679	4	125.670	0.226	0.9240
DEMAND * UNIQUE	57706.602	1	57706.602	103.676	0.0000
TREATMENT * DEMAND * UNIQUE	913.304	4	228.326	0.410	0.8013
REPAIR * DEMAND * UNIQUE	51480.919	1	51480.919	92.491	0.0000
TREATMENT * REPAIR * DEMAND * UNIQUE	763.904	4	190.976	0.343	0.8488
Error	244906.750	440	556.606		
Total	834087.000	480			
Corrected Total	705084.5813	479			

R Squared = .653 (Adjusted R Squared = .622)

The results suggest that at around 0.027 level of significance the H_o should rejected and it is suspected that at least one of the treatment means were not equal.

After suspecting that the treatment means differ, and therefore that the factors somehow affect the mean response, one should determine how the factors affect the mean response. The following test was conducted:

H_o: Factors of repairability, demandability and uniqueness do not interact to affect the response mean

H_a: Factors of repairability, demandability and uniqueness do interact to affect the response mean

The results suggest that at around 0.000 level of significance the H_0 should rejected and it is suspected that the factors affect the forecasting error.

Because the factors interact, there is difficulty in testing the main effects for repairability, demandability and uniqueness. Instead, the treatment means were compared in an attempt to learn the nature of their interaction. Rather than compare all 40 pairs of treatment means, the differences between the forecasting methods were studied using a Bonferroni test [Table 12]. However, the results must be interpreted with caution since the Bonferroni test shares the same assumptions as ANOVA does.

Table 12. Bonferroni Test for Multiple Comparisons

Bonferroni Test

(I) Forecasting Method	(J) Forecasting Method	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Expon	D.Expon Brown	-7.5104	3.405	0.279	-17.118	2.097
	Mov Avg	2.3438	3.405	1.000	-7.263	11.951
	Autoregres	2.1042	3.405	1.000	-7.503	11.711
	Linear Regression	-0.2083	3.405	1.000	-9.816	9.399
D.Expon Brown	Expon	7.5104	3.405	0.279	-2.097	17.118
	Mov Avg	9.854*	3.405	0.040	0.247	19.461
	Autoregres	9.614*	3.405	0.050	0.007	19.222
	Linear Regression	7.3021	3.405	0.326	-2.305	16.909
Mov Avg	Expon	-2.3438	3.405	1.000	-11.951	7.263
	D.Expon Brown	-9.854*	3.405	0.040	-19.461	-0.247
	Autoregres	-0.2396	3.405	1.000	-9.847	9.368
	Linear Regression	-2.5521	3.405	1.000	-12.159	7.055
Autoregres	Expon	-2.1042	3.405	1.000	-11.711	7.503
	D.Expon Brown	-9.614*	3.405	0.050	-19.222	-0.007
	Mov Avg	0.2396	3.405	1.000	-9.368	9.847
	Linear Regression	-2.3125	3.405	1.000	-11.920	7.295
Linear Regression	Expon	0.2083	3.405	1.000	-9.399	9.816
	D.Expon Brown	-7.3021	3.405	0.326	-16.909	2.305
	Mov Avg	2.5521	3.405	1.000	-7.055	12.159
	Autoregres	2.3125	3.405	1.000	-7.295	11.920

Based on observed means.

* The mean difference is significant at the .05 level.

Observing the Bonferroni test for multiple comparisons, the mean difference of double exponential smoothing is significant at the 0.05 level from the mean difference of the moving average and the autoregression method. However, the confidence intervals showed that all forecasting methods overlapped each other. Based on this information, one should suspect that there was not significant evidence to say that the forecasting methods were different from each other.

Therefore, the data used for assessing the forecasting performance did not provide enough statistical power to determine the effects during the interactions because the assumptions for normality and equal variances were not met. These results led to performing a non-parametric test.

Non-Parametric Test

In this section we considered the problem of analyzing several related samples to detect differences in k possible different treatments, where K>=2. The observations were arranged in blocks, which are groups of k experimental units similar to each other in some important respects (such as the forecasting techniques). These techniques may tend to respond to a particular stimulus, the categories of part number, in different way under different measures of accuracy.

The suggested test is the Friedman test, equivalent of a one-sample repeated measures design or a two-way analysis of variance with one observation per cell [Conover, 1980: 298-302]. Friedman tests the null hypothesis of no treatment differences. The test statistic depends only on the ranks of the observation within each block. This test is an extension of the sign test. Therefore, the power of the Friedman test is useful for a small number of treatments. If the number of treatments appear to be five or more, this test appears to be more powerful than the Quade test [Conover, 1980: 298-302].

The purpose of the Friedman Multiple Rank tests is to compare ranked performance between levels of critical factors. The assumptions necessary to assure the validity of this test are as follows:

- The b k-variables are mutually independent. (The results within one block do not influence the results within the other blocks)
- Within each block the observations may be ranked according to some criterion of interest. In this particular case, it is important to determine which forecasting technique performs better for each category of part number. The best measure of accuracy is ranked as 1.
- The sample range may be determined within each block so that the blocks may be ranked.

The hypothesis to be tested is:

- Ho: Each ranking of the measures of accuracy within each block is equally likely. (i.e. the treatments have identical effects)
- Ha: At least one of the forecasting techniques tends to yield a larger observed values than at least one other treatment

Test Statistics: For convenience, first calculate the terms

$$A_2 = \sum_{i=1}^{b}\sum_{j=1}^{k}[R(X_{ij})]^2 \tag{18}$$

$$B_2 = \frac{1}{b}\sum_{j=1}^{k} R_j^2 \text{, where } R_j = \sum_{i=1}^{b} R(X_{ij}) \tag{19}$$

$$T_2 = \frac{(b-1)[B_2 - bk(k+1)^2/4}{A_2 - B_2} \tag{20}$$

Decision Rule: Reject the null hypothesis at the level α if T_2 exceeds the 1-α quartile of the F distribution with K_1=K-1 and K_2=(b-1)(k-1).

Multiple comparisons: This method for comparing individual treatments will be used only if the Friedman test results in rejection of the null hypothesis. Treatments i and j are considered different if the following inequality is satisfied:

$$|R_j - R_i| > t_{1-\alpha/2}\left[\frac{2b(A_2 - B_2)}{(b-1)(k-1)}\right]^{\frac{1}{2}} \tag{21}$$

Based on the previous formula, one Friedman test was performed for each factor combination (individual part number). For the purpose of the methodology, the calculation for the part representing a consumable-low demand-common item (p/n 307) is presented in Table 13. The overall null hypothesis was rejected; at least one forecasting technique differed in rank performance from another at a 0.01 confidence level.

The second part (multiple comparison) indicates which of the treatments can be separated into groups based on a critical t selected with 99% of confidence. In this case, forecasting method 2 and forecasting method 1 had better performance, and were different from forecasting methods 3, 4 and 5, and that forecasting method 5 was also different from 3 and 4. The same procedure was performed for the remaining parts [see Appendix D] and the results obtained are summarized in Table 13.

Table 13. Non-parametric Friedman Test for P/N 307

	Data	1	2	3	4	5	$[R(X_{ij})]^2$
Quantity No.2	CFE	2	1	3	4	5	55
	ME	2	1	3	4	5	55
307	MAD	2	1	3	4	5	55
Consumable	MSE	1	2	3	4	5	55
Low demand	Rj	7	5	12	16	20	220
Common	Rj^2	49	25	144	256	400	
	ΣRj^2	874					

H_0:All Forecasting Techniques are equal

b=	4	A_2=	220
k=	5	B_2=	218.5
K_1=	4	T_2=	77.00 (T statitstics)
K_2=	12	F (α, K_1, K_2)=	5.412 (critical value)
		Overall p-value=	0.010
		Reject H_0 ?	Yes (T_2>F)

α	$t_{1-\alpha/2,k2}$	$T_{critical}$	MULTIPLE COMPARISON					
0.99	3.05454	3.055	Treat	Rank	I	II	III	IV
R> $T_{critical}$; next level			F2	5	A			
Note: Adapted from Conover, J. 1980: 300			F1	7	A			
$\mid R_{fn-1} - R_f \mid > t_{1-\alpha/2}\left[\frac{2b(A_2-B_2)}{(b-1)(k-1)}\right]^{\frac{1}{2}}$			F3	12		B		
			F4	16			C	
			F5	20				D

Analyzing the summary table, it can be said that at least one forecasting method was different from the others for all factor combinations, except for repairable-high-specific. However, there was not enough statistical power to determine the real performance of the forecasting techniques under the influence of the eight levels of the three factors.

Based on the results obtained from the parametric statistical analysis, ANOVA, and the non-parametric tests (Friedman), it can be concluded that the experiment did not provide enough statistical power to draw accurate conclusions. These results led to the simulation of new data points to get more statistical power for conducting this experiment.

Table 14. Non-Parametric Friedman Test Summary

SUMMARY TABLE MULTIPLE RANK TEST								$t_{1-0.99/2,1119}$	3.05	α	0.99				
Category	$T_{critical}$	Treat	Rank	I	II	III	IV	Category	$T_{critical}$	Treat	Rank	I	II	III	IV
Consumable	10.13	F2	6	A				Consumable	9.82	F3	6	A			
Low demand		F3	10	A	B			High demand		F2	9	A	B		
Specific		F1	11	A	B			Specific		F4	12	A	B	C	
		F4	14	A	B					F1	14	A	B	C	
		F5	19		B					F5	19			C	
Consumable	3.05	F2	5	A				Consumable	2.49	F1	6	A			
Low demand		F1	7	A				High demand		F3	6	A			
Common		F3	12		B			Common		F4	12		B		
		F4	16			C				F2	16			C	
		F5	20				D			F5	20				D
Repairable	34.54	F2	6	A				Repairable	34.85	F5	4	A			
High demand		F1	7	A				Low demand		F1	9	A			
Common		F4	11	A				Common		F4	12	A			
		F3	16	A						F2	17	A			
		F5	20	A						F3	18	A			
Repairable	35.12	F2	8	A				Repairable	35.16	F3	4	A			
High demand		F1	8	A				Low demand		F1	11.5	A			
Specific		F3	10	A				Specific		F2	12.5	A			
		F5	16	A						F4	16	A			
		F4	18	A						F5	16	A			

Phase 3- Prepare and Perform the Simulation Experiment

The goal of this simulation experiment is to obtain point and interval estimates of the parameters of interest for the different forecasting techniques, to compare these techniques conceptually and statistically, and to draw inferences about the treatment effects. The most important parameters to quantify the performance of the forecasting methods were the forecast errors. The forecast errors parameters were the cumulative forecasting error, CFE, the mean error, ME, the mean absolute deviation, MAD, and the mean squared error, MSE.

Up to this point, the experiment compared the performance of five forecasting techniques on 4 parameters (CFE, ME, MAD, and MSE). However, for the purpose of the simulation only four forecasting techniques were used. They are single exponential smoothing, double exponential, moving average, and autoregression. The linear regression was not going to be simulated for several reasons. First, in 7 out of 8 cases the performance was the worst. In addition, there would be no data to use for the explanatory variables, hours and cycles.

The study is interested in determining the bias and the deviation of the errors. The ME is a measure of bias, and the MAD and MSE measure the deviation. The CFE is not going to be used for the statistical tests because it provides similar information to the ME.

Model Conceptualization

In essence, the researcher is interested in simulating additional demand of aircraft spare parts [Figure 4]. This was based on the theoretical distribution of the irregular component that was observed after the decomposition of the time series that corresponds to historical demand data. Using the Rnguniform Excel function, new irregular component data points were generated. After that, the seasonal and trend cycle was added to obtain the simulated demand data.

The parameters that best fit the different forecasting methods were calculated using the information provided on the historical demand data that corresponds to 24 periods. Once the parameters were determined, the next step was to calculate the CFE, ME, MAD, and MSE.

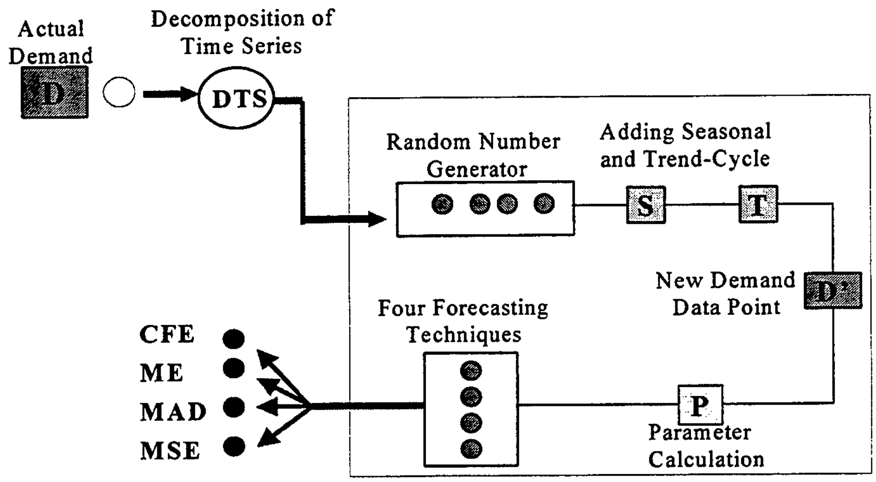


Figure 4. Model Conceptualization

Time Series Decomposition

The procedure of decomposition is performed because the researcher is interested in reproducing the demand pattern in a simulation model. Many forecasting methods are based on the concept that when an underlying pattern exists in a data series, that pattern can be distinguished from randomness by smoothing past values. The effect of this smoothing is to eliminate randomness so the pattern can be projected into the future and used as the forecast [Makridakis, 1997: 86].

Decomposition methods usually try to identify two separate components of the basic underlying pattern that characterize the time series. These are the trend-cycle and the seasonal factors. The seasonal factor relates to periodical fluctuations of constant length that are caused for the month of the year, timing of holidays, and corporate policies. The trend-cycle represents longer-term changes in the level of the series. Decomposition assume that the data pattern are made up as follows:

Data = pattern + error

Data = f(trend-cycle, seasonality, error)

The basic approach in such decomposition is empirical and consists of first removing the trend-cycle, then isolating the seasonal component. Any residual is assumed randomness, or an irregular component in the time series. This irregular component can not be predicted, but can be identified. From a statistical point of view there are a number of theoretical weaknesses in the decomposition approach; however, in real life situations it has been used with success [Makridakis, 1997: 87].

Decomposition methods can be classical decomposition, census bureau method, and seasonal trend STL method. For the purpose of this study we will focus on the classical decomposition method because of its simplicity.

The classical decomposition can take the form of additive or multiplicative model. An additive model is appropriate if the magnitude of the seasonal fluctuations does not vary with the level of the series. However, if the seasonal fluctuations increase and decrease proportionally with increases and decreases in the level of the series, then a multiplicative model is appropriate [Makridakis, 1997: 88].

Therefore, to decompose the time series of the eight (8) part numbers proposed this study will assumed that the time series is additive with monthly seasonal periodicity. For the clarity of the process followed during the decomposition, the same mechanics of showing the process for one part number will be used [see Table 15]. A classical decomposition can be carried out using the following four steps [Makridakis, 1997: 107]:

Table 15. Classical Decomposition, Additive Model

CONS-L-S Month	P/N 61-0478-9 Obs (Yt)	Trend 12 MA (Tt)	Detrend Yt-Tt	Seasonal St	Irregular Et
Jan-96	0	4.3077	-4.3077	1.4712	-5.7788
Feb-96	0	6.9333	-6.9333	-4.0083	-2.9250
Mar-96	0	6.1176	-6.1176	-8.6005	2.4828
Apr-96	0	7.6842	-7.6842	-3.4254	-4.2588
May-96	14	7.6190	6.3810	1.8155	4.5655
Jun-96	14	6.9565	7.0435	8.3967	-1.3533
Jul-96	0	8.2500	-8.2500	-4.5163	-3.7337
Aug-96	24	9.2500	14.7500	9.2798	5.4702
Sep-96	0	9.2500	-9.2500	-10.7303	1.4803
Oct-96	21	10.4167	10.5833	10.9681	-0.3848
Nov-96	7	11.2500	-4.2500	-0.9250	-3.3250
Dec-96	0	11.9167	-11.9167	-12.5353	0.6186
Jan-97	19	11.7500	7.2500	1.4712	5.7788
Feb-97	12	13.0833	-1.0833	-4.0083	2.9250
Mar-97	0	11.0833	-11.0833	-8.6005	-2.4828
Apr-97	14	13.1667	0.8333	-3.4254	4.2588
May-97	10	12.7500	-2.7500	1.8155	-4.5655
Jun-97	22	12.2500	9.7500	8.3967	1.3533
Jul-97	12	12.7826	-0.7826	-4.5163	3.7337
Aug-97	16	12.1905	3.8095	9.2798	-5.4702
Sep-97	0	12.2105	-12.2105	-10.7303	-1.4803
Oct-97	25	13.6471	11.3529	10.9681	0.3848
Nov-97	16	13.6000	2.4000	-0.9250	3.3250
Dec-97	1	14.1538	-13.1538	-12.5353	-0.6186

Step 1. The trend cycle is computed using a centered 12 moving average. In this case a centered moving average is not an odd number for all the periods. Generally, the form of the center moving average for 22 months is as follows:

1/12 [0.5,1,1,1,1,1,1,1,1,1,1,0.5]

In the case where one observation is missing, it will be reduced using the same weight for the moving average.

Step 2. The de-trended series is computed by subtracting the trend-cycle component from the data, leaving the seasonal and irregular terms. That is,

$$Y_t - T_t = S_t + E_t \tag{22}$$

Step 3. Once the trend-cycle component has been removed, the seasonal component is estimated by averaging the value for each of the corresponding periods in the data. In other words, the seasonal index for period 1, or January, is the average of all the de-trended values for period 1, and so on. It is assumed that the seasonal component is constant for every period within the years of study.

Step 4. Finally, the irregular series E_t is computed by subtracting the estimated seasonality, trend, and cycle from the original data series. A graphical representation of all the four steps described above is presented in Figure 5. In this graph, it is very easy to detect the trend-cycle and the seasonality. Similar procedures of decomposition for the remaining part numbers included in this study are in Appendix E " Decomposition of Historical Demand Data".

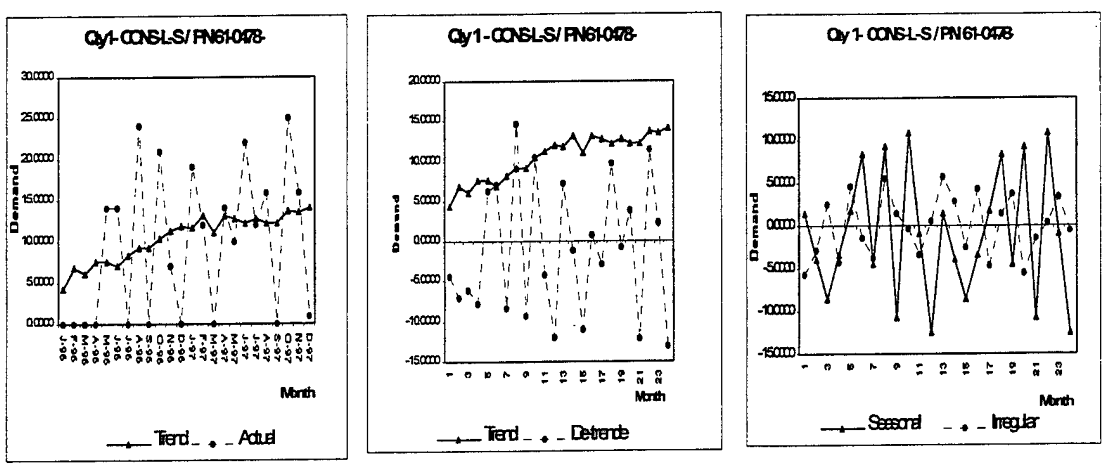


Figure 5. Analysis of Time Series Component in Actual Data

Underlying Statistical Distribution

Based on the results obtained from the decomposition method, and the shape of the irregular component, the theoretical probability distribution in all the cases was a uniform distribution and the parameters of the underlying distributions are summarized in Table 16.

Table 16. Parameters of the Theoretical Uniform Distributions

Quantity	Part Number	Name	Category	Minimum	Maximun
1	61-04789	Battery Ni-Cad	CONS-L-S	-5.78	5.78
2	307	Light	CONS-L-C	-12.40	12.40
3	F1815/WW/RS	Bulb lamp	CONS-H-S	-14.23	14.23
4	MS24665-134	Pin Cotter	CONS-H-C	-154.51	154.51
5	ZP650-SC-M-B-3	Oxigen Bottle	REP-H-C	-4.15	4.15
6	2-1517	Brake Assy	REP-H-S	-2.01	2.01
7	622-2362-001	ADF Receiver	REP-L-C	-1.94	1.94
8	DH1030-24-600CS	Inverter	REP-L-S	-3.31	3.31

To validate the hypothesized uniform distribution of the irregular component, a goodness-of-fit-test using a Kolmogorov-Smirnov test was performed [Table 17] because it is particularly useful when sample sizes are small [Banks, 1997: 409].

In order to eliminate the negative numbers from the actual irregular component, a quantity of 160 was added to move the distribution without affecting the original pdf and cdf of the original irregular component. Similar procedures performed with the remaining part numbers are located in Appendix F " Kolmogorov Test for the Uniform Distribution".

Table 17. Test for the Uniform Distributions Using a Kolmogorov Test

I	Transformed	Ranked	Normalized	I/N	D^+	D-
1	154.2212	154.221	0.040	0.04	0.0015	0.040
2	157.0750	154.530	0.080	0.08	0.0029	0.039
3	162.4828	155.435	0.121	0.13	0.0041	0.038
4	155.7412	155.741	0.161	0.17	0.0052	0.036
2	164.5655	156.266	0.202	0.08	0.0000	0.035
6	158.6467	156.675	0.243	0.25	0.0071	0.160
7	156.2663	157.075	0.284	0.29	0.0078	0.034
8	165.4702	157.517	0.325	0.33	0.0085	0.033
9	161.4803	158.520	0.366	0.38	0.0089	0.033
10	159.6152	158.647	0.407	0.42	0.0092	0.032
11	156.6750	159.381	0.449	0.46	0.0094	0.032
12	160.6186	159.615	0.491	0.50	0.0095	0.032
13	165.7788	160.385	0.532	0.54	0.0094	0.032
14	162.9250	160.619	0.574	0.58	0.0092	0.032
15	157.5172	161.353	0.616	0.63	0.0089	0.033
16	164.2588	161.480	0.658	0.67	0.0085	0.033
17	155.4345	162.483	0.701	0.71	0.0078	0.034
18	161.3533	162.925	0.743	0.75	0.0071	0.035
19	163.7337	163.325	0.785	0.79	0.0062	0.035
20	154.5298	163.734	0.828	0.83	0.0052	0.036
21	158.5197	164.259	0.871	0.88	0.0041	0.038
22	160.3848	164.565	0.914	0.92	0.0029	0.039
23	163.3250	165.470	0.957	0.96	0.0015	0.040
24	159.3814	165.779	1.000	1	0.0000	0.042
	Sum	3840		MAX	0.009473122	0.159601034

H_0 : Irregular component is uniform distributed

D = 0.159601034 D(a,N) = 0.277608838 (critical value)

α = 0.05 Reject H_0? NO (D< D(a,N))

N= 24

Simulation of Actual Demand Data.

To verify and validate the model the following steps were accomplished before the simulation of the complete data for the experiment:

1. Generate 24 random data points using the underlying statistical distribution of the irregular component obtained from the time series decomposition. The random number are generated using the excel function Rnguniform (min, max) with the parameters previously established from the irregular component of the actual demand, observed from historical data.

2. Aggregation of the seasonal component and trend-cycle component to previous random numbers to obtain 24 simulated demand data points. To add the trend component, a regression line was calculated for the de-trended values. Finally, a new actual simulated demand data where $Y'_t>=0$ is obtained [Table 18]. The remaining calculations are in Appendix G " Transformation of Simulated Demand Data".

Table 18. Procedure to Obtain Actual Simulated Demand Data

		Model Coefficients for the De-trend component					
Excel Formula=Rnguniform(min,max)		Bo	5.94775	B1	0.366245		
CONVERSION OF SIMULATED IRREGULAR COMPONENT DATA TO ACTUAL SIMULATED DATA							
Month	**Period**	**E't**	**St**	**Bo**	**B1**	**Y't**	**Y't(Trunc,0)**
Jan-96	1	2.3852	1.4712	5.948	0.3662	10	10
Feb-96	2	5.1942	-4.0083	5.948	0.7325	8	8
Mar-96	3	-0.7794	-8.6005	5.948	1.0987	-2	0
Apr-96	4	-0.9326	-3.4254	5.948	1.4650	3	3
May-96	5	-2.6145	1.8155	5.948	1.8312	7	7
Jun-96	6	-4.5707	8.3967	5.948	2.1975	12	12
Jul-96	7	3.3628	-4.5163	5.948	2.5637	7	7
Aug-96	8	-3.4038	9.2798	5.948	2.9300	15	15
Sep-96	9	-1.3666	-10.7303	5.948	3.2962	-3	0
Oct-96	10	-0.3378	10.9681	5.948	3.6625	20	20
Nov-96	11	1.4849	-0.9250	5.948	4.0287	11	11
Dec-96	12	0.1918	-12.5353	5.948	4.3949	-2	0
Jan-97	13	1.7204	1.4712	5.948	4.7612	14	14
Feb-97	14	0.9680	-4.0083	5.948	5.1274	8	8
Mar-97	15	-3.0647	-8.6005	5.948	5.4937	0	0
Apr-97	16	-0.0412	-3.4254	5.948	5.8599	8	8
May-97	17	2.5364	1.8155	5.948	6.2262	17	17
Jun-97	18	-5.5323	8.3967	5.948	6.5924	15	15
Jul-97	19	1.9986	-4.5163	5.948	6.9587	10	10
Aug-97	20	5.7176	9.2798	5.948	7.3249	28	28
Sep-97	21	-3.6325	-10.7303	5.948	7.6911	-1	0
Oct-97	22	-5.2219	10.9681	5.948	8.0574	20	20
Nov-97	23	0.0910	-0.9250	5.948	8.4236	14	14
Dec-97	24	-5.6394	-12.5353	5.948	8.7899	-3	0

3. Validation of the actual simulated demand data using a paired T-test. The paired T-test was performed against the actual demand data observed from historical data. The

null hypothesis developed is that the two populations are different at a 0.05 level. The procedure to perform the paired T-test is showed in table 19. The remaining calculations are in Appendix H "Comparison of Actual Demand versus Simulated Demand".

Table 19. Paired T-test to Compare Simulated Demand versus Actual Demand

COMPARISON OF ACTUAL DATA AND SIMULATED DATA (PAIR T-TEST)				
P/N 61-0478-9 CONS-L-S	Historical Data Obs (Yt)	Model Data Sim(Y't)	Observed Difference dj	Squared Deviation From Mean $(dj-d^{\wedge})^2$
Jan-96	0	10	-10	101.71
Feb-96	0	8	-8	60.54
Mar-96	0	0	0	0.01
Apr-96	0	3	-3	8.82
May-96	14	7	7	50.48
Jun-96	14	12	2	4.47
Jul-96	0	7	-7	52.89
Aug-96	24	15	9	87.08
Sep-96	0	0	0	0.01
Oct-96	21	20	1	0.71
Nov-96	7	11	-4	11.91
Dec-96	0	0	0	0.01
Jan-97	19	14	5	26.88
Feb-97	12	8	4	16.41
Mar-97	0	0	0	0.01
Apr-97	14	8	6	33.00
May-97	10	17	-7	41.48
Jun-97	22	15	7	44.63
Jul-97	12	10	2	2.88
Aug-97	16	28	-12	148.47
Sep-97	0	0	0	0.01
Oct-97	25	20	5	28.45
Nov-97	16	14	2	6.49
Dec-97	1	0	1	1.18
H_0 : The two populations are different		Sum	-0.08519	728.52

S^2d	31.6746	$\alpha=$	0.05	
$d^{\wedge}$	-0.0035	T statistics (To)	0.0005	
N=	24	$t_{0.05/2,k-1}$	2.3979	(critical value)
		Reject H_0?	Yes	$(T_o< t_{(\alpha,N-1)})$

Best Fit Parameters Calculations

After the null hypothesis of the paired T-Test was rejected, the next step was to find the forecasting parameters for each forecasting technique using the same procedure described in phase two. The only difference with the procedure performed in phase two was that all the 24 periods available from actual demand data were used to calculate the parameters instead of 12. The parameters that best fit each forecasting technique for each part number are as follows [Table 20]:

Table 20. Forecasted Demand Parameters Using Simulated Demand Data

Parameters Used for Forecasting Based on 24 Periods							
No.	Reparability	Demand	Uniqueness	F1	F2	F3	F4
1	Consumable	Low	Specific	0.6	0.1	5	Lag 1,3
2		Low	Common	0.4	0.3	5	Lag 1,2,3
3		High	Specific	0.3	0.8	5	Lag 1,2,3
4		High	Common	0.4	0.7	5	Lag 1,3
5	Repairable	High	Common	0.1	0.4	4	Lag 1,2,3
6		High	Specific	0.6	0.2	8	Lag 1,2,3
7		Low	Common	0.1	0.5	9	Lag 1
8		Low	Specific	0.3	0.3	8	Lag 3

Analyzing the results, the α values and moving averages for single exponential, double exponential and moving averages were the same values presented in phase two with only 12 periods. The changes occurred in calculating the parameters for the autoregression model [Table 21] because the lags of 1, 2 and 3 included more periods.

Table 21. Parameters For The Autoregression Model

Coefficients Used in the Autoregression Model				
Category	β_0	$\beta\tau_{-1}$	$\beta\tau_{-2}$	$\beta\tau_{-3}$
Qty1	13.361	-0.458		0.27
Qty2	1.793	-0.547	-0.134	0.07025
Qty3	11.607	0.022	0.3650	-0.102
Qty4	245.765	-0.232		0.207
Qty5	3.083	0.723	-0.251	
Qty6	2.523	0.055	-0.2340	0.157
Qty7	0.948	0.182		
Qty8	1.045			-0.164

Pilot and Production Runs

A pilot experiment consisting of 30 runs of 60 periods each was performed to assess the initialization bias of the forecasting performance for each of the eight levels of the three factors across the 4 forecasting methods selected.

The parameters of interest during each run were the forecasting errors, measured in terms of the ME, MAD and MSE. To guarantee independence of the forecasting error obtained from simulated demand data, a method of batch means was used because the problem stated previously with the autoregression model (violation of independence). In addition, the random seed was changed every time the batch was obtained. Moreover, to eliminate the initialization bias it was considered that the first 24 periods were enough to warm up the simulation and eliminate possible bias.

According to Banks [1997: 464], the method of batch means attempts to solve the problem with dependence by dividing the output data from one replication into a few large batches, and then treating the means of these batches as if they were independent. If the batch mean is sufficiently large, k=30, successive batch means will be approximately independent.

After knowing the fact that the batch means method used for the pilot run are approximately independent, the next step was to determine the length of the simulation run. The usual method for estimating the needed length of the simulation run was to perform a few short trial runs, 30 replications of 36 periods each, to calculate the mean and standard deviation of the forecast errors, measure in terms of the MAD.

Summary

This chapter discussed the approach to evaluate the performance of the different forecasting techniques selected for the study. Four analytical phases are used, but only the first three was presented in this chapter:

1. The first phase consisted of the identification of the characteristics of the aircraft spare parts, and determining the forecasting techniques to be used.

2. The second phase consisted of measuring the performance of the forecasting techniques, subject to historical demand data.

3. The third phase consisted of preparing and performing the simulation experiment to determine the best forecasting technique under each individual scenario.

This chapter provided a description on the type of research design, the research questions, the null hypothesis, and the instruments used to do the comparison analysis. It also presented the analytical approach, population size, sample size, data collection, assumptions, and limitations used to perform the study. Finally, the chapter highlighted and explained the implementation of the research plan. The next chapter presents the fourth phase of this simulation experiment and the analysis of the data obtained.

IV. Results and Analysis

Introduction

This chapter presents the results and analysis of the fourth phase of the research as well as the comparison between current management techniques and the forecasting system proposed. The chapter is separated into four sections. The first section describes the number of replications required to draw conclusions with enough confidence. The second section discusses the results of the different forecasting methods respective to the forecast error measure (ME, MAD and MSE) using an ANOVA test. The third section discusses the results obtained from non-parametric test for each part number individually using the Friedman Test, if previous tests fail. The fourth section discusses the analysis of the current management techniques versus the performance of the different forecasting techniques. Finally, the chapter gives a conclusion and a summary of the chapter.

Phase 4- Simulation of Additional Demand Data

Determination of Number of Replications

Assuming that the forecasting error is normally distributed, the length of the simulation run (number of replications) can be determined for a given accuracy and a statistical confidence level. The following formula can be used to determine the required length of the simulation run [Banks, 1997: 447]:

$$R \geq \left(\frac{t_{\alpha/2,R-1} S_0}{\varepsilon} \right) \qquad (23)$$

where

R= Number of replications

$t_{\alpha/2,R-1}$ = Confidence level

S= Standard deviation

E= Error criterion

The R_0 replications will be used to obtain an initial estimate S^2_0 of the population variance S^2. To meet the half-length criterion, a sample size R must be chosen such that $R>=R_0$. The half length of the confidence interval should be approximately ε or smaller. This formula (23) was used to determine how many replications were needed to obtain a 95% confidence interval with ± 5% of accuracy. Enough replications must be generated to ensure the output parameter, MAD, is accurate and precise enough to establish real differences between the treatment and factor combinations. According to Tersine (1994: 43), MAD is the measure most desirable when comparing different forecasting techniques because it has the greatest degree of accuracy. For the initial calculation a value of 30 replications was used. Each replication is the mean value of a batch run of 60 (only 36 useful data points) simulated data points. The first 24 data points were considered part of the warm-up and were not included in the data calculation.

Table 22 presents the computations for one part number, and the remaining are located in Appendix I "Desired Number of Replications for The Simulation Model. " In this case the initial number of replications was more than sufficient to ensure the desired accuracy and precision. Seventeen replications were enough to meet the accuracy rule (± 5%).

Table 22. Replications Required for Each Part Number and Forecasting Combination

Part Number 61-0478-9

Forecasting Method: Single Exponential

Goal: Error of +-		0.05 mean
R_i	MAD_i	
1	8.78	
2	9.24	
3	9.07	
4	9.06	
5	8.01	
6	9.21	
7	8.79	
8	9.76	
9	8.36	
10	10.31	
11	9.35	
12	10.06	
13	9.87	
14	9.62	
15	6.65	
16	10.03	
17	9.29	
18	10.10	
19	10.27	
20	7.74	
21	8.63	
22	9.20	
23	8.52	
24	7.97	
25	8.89	
26	8.00	
27	9.38	
28	9.21	
29	8.24	
30	10.05	

Avg-MAD = 9.0560 note: Avg-MAD = sum(MAD_i)/R

S_a^2= 0.745 note: S_a^2 = sum(MAD_i-Avg_{MAD})^2/(R-1)

S_a^2/R= 0.025 note: var = S_a^2/R

std dev = 0.158 note: std dev = $(S_a^2/R)^{0.5}$

R = 30

alpha = 0.05

Confidence interval: avga +,- t(alpha/2, R-1) * std dev

Using Excel function Tinv, $t_{(0.025, 29)}$ = **2.05**

	LCL		Mean		UCL
and so	8.734	<=	9.06	<=	9.378
confidence interval is +,-			0.322		

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?

Assumption: sample variance **won't** change much!

note: **epsilon** = $(t_{(alpha/2, R-1)})$(std dev) = $(t_{(alpha/2, R-1)})$*S/$(R^{0.5})$

so.. $R^{0.5} = t_{(alpha/2, R-1)}$*S/epsilon, and so R = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

Let Ro be the sample of **30** replications already made, and let $S_o^2 = S_a^2$ = **0.745**

Hence, S_o = **0.8632**

So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2,R-1)}$*S/epsilon$)^2$

R	$t_{(.025,R-1)}$	X
30	2.05	15.203
20	2.09	15.922
17	**2.12**	**16.333**

Epsilon 5% **0.45**

Hence, perform about R-Ro =

R_o= 30

R= 17

$R-R_o$= -13

The summary of the results obtained from each particular calculation is presented in Table 23. Except for the consumable-low demand-common item, the initial 30 replications were sufficient. However, the corresponding epsilon value for ± 5% of variation with respect to the mean is low, only 0.11. This small value was considered small enough for forecasting accuracy; therefore, the full number of replications would not be required.

Table 23. Summary of Number of Replications Required

Epsilon 5%μ		Single Exponential					Moving Average				
R_0	30	R	$t_{(.025,R-1)}$	X	$R-R_0$	Epsilon	R	$t_{(.025,R-1)}$	X	$R-R_0$	Epsilon
Qty1	CONS-L-S	17	2.12	16	-13	0.45	16	2.131	15	-14	0.38
Qty2	CONS-L-C	95	1.99	94	65	0.11	93	1.986	91	63	0.11
Qty3	CONS-H-S	21	2.09	20	-9	0.51	19	2.101	18	-11	0.50
Qty4	CONS-H-C	25	2.06	23	-5	4.24	24	2.069	23	-6	4.20
Qty5	REP-H-C	9	2.31	7	-21	0.30	8	2.365	7	-22	0.33
Qty6	REP-H-S	4	3.18	3	-26	0.33	5	2.776	3	-25	0.28
Qty7	REP-L-C	5	2.78	3	-25	0.19	5	2.776	4	-25	0.21
Qty8	REP-L-S	9	2.31	7	-21	0.24	9	2.306	8	-21	0.24
Epsilon 5%μ		Double Exponential					Autoregression				
R_0	30	R	$t_{(.025,R-1)}$	X	$R-R_0$	Epsilon	R	$t_{(.025,R-1)}$	X	$R-R_0$	Epsilon
Qty1	CONS-L-S	4	3.18	2	-26	1.05	6	2.571	4	-24	0.60
Qty2	CONS-L-C	93	1.99	91	63	0.13	72	1.994	71	42	0.13
Qty3	CONS-H-S	19	2.10	17	-11	2.87	14	2.160	12	-16	0.61
Qty4	CONS-H-C	25	2.06	23	-5	5.53	20	2.093	19	-10	6.26
Qty5	REP-H-C	5	2.78	4	-25	0.40	9	2.306	8	-21	0.42
Qty6	REP-H-S	5	2.78	2	-25	0.31	5	2.776	3	-25	0.25
Qty7	REP-L-C	5	2.78	3	-25	0.34	3	4.303	10	-27	0.18
Qty8	REP-L-S	9	2.31	8	-21	0.21	10	2.262	7	-20	0.20

The desired length of the simulation was decided to be 50 replications. This number should be large enough to provide sufficient statistical power for the factorial design. According to the initial length of the pilot run, it was necessary to run an additional 20 replications to complete the length required for the experiment. The complete set of simulation output is in Appendix J "Forecasting Errors Using Simulated Demand Data".

Analysis of Forecasting Performance

ANOVA Results

The ANOVA was performed for each of the three parameters representing the forecasting errors, the ME, MAD, and MSE. The ME provides a measure of bias by averaging the individual errors in the simulation batch. A positive ME indicates a tendency to under-forecast, while a negative ME indicates a tendency to over-forecast. The MAD and the MSE measure the magnitude of the deviation of the forecast. The difference between the two, MAD and MSE, are that MAD weights all errors equally, while the other weights error in proportion to the squared values. The MSE, unlike the MAD, penalizes a forecasting technique more heavily for larger errors than for smaller ones [Tersine: 1994: 43].

Before accepting the conclusions of the analysis of variance, the diagnostics must be performed to check the assumptions of the model (residual analysis). The residuals for the ME, MAD, and MSE are shown in Figure 6 and 7. The normal probability plot and dot diagram of these residuals reveals that the residuals are not normally distributed [Figure 6].

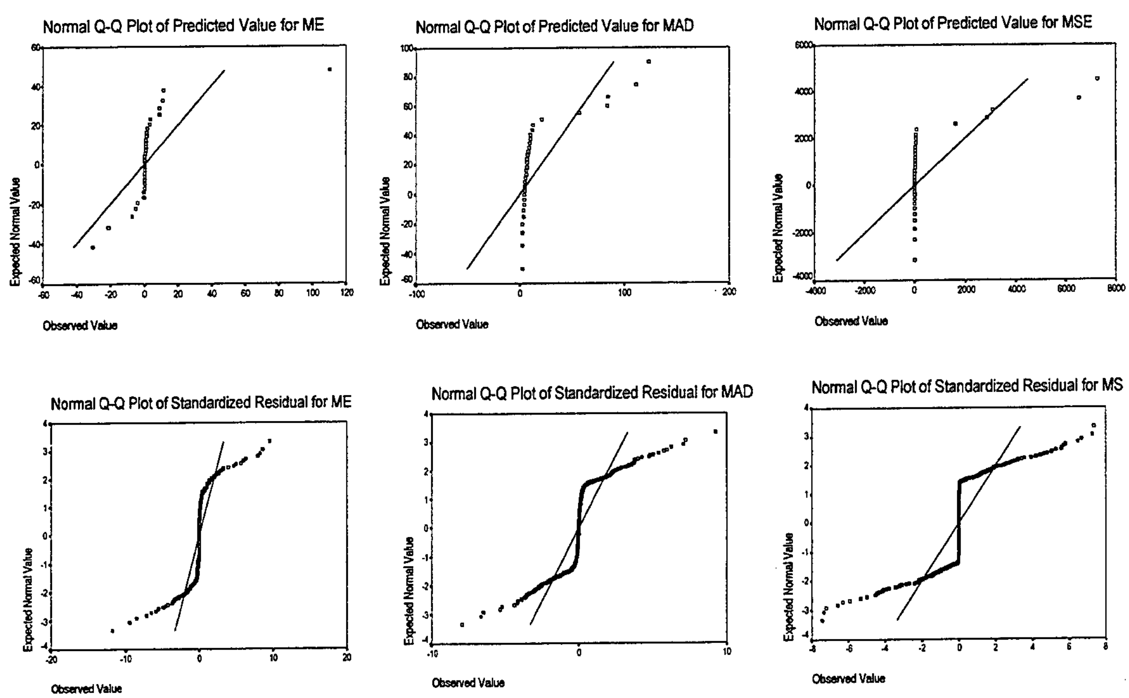


Figure 6. Normal Probability Plots for Predicted and Residuals Values

Plotting the residuals versus the predicted values indicated a high tendency for the variance of the residuals to increase as the quantities predicted increase. This demonstrates a failure of the assumptions of equality of variance [Figure 7]. Therefore, the assumptions necessary for the validity of the ANOVA tests (normality and equal variances) are not being satisfied.

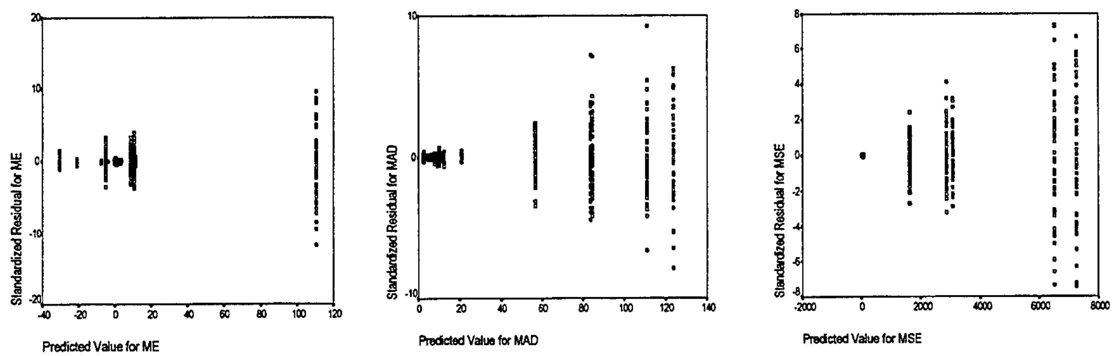


Figure 7. Residuals versus Predicted Values

If these assumption are not met, then the analysis of variance procedure is not an exact test of the hypothesis of no difference in treatment means. Consequently, it is usually unwise to rely on the analysis of variance until the assumptions have been validated [Montgomery: 1997: 79-80]. Even though the ANOVA assumptions were not met the ANOVA results are presented to gain a general understanding about the performance of the forecasting methods [Table 24].

The first test was:

H_o: No performance differences between treatments in $F_1, F_2, \ldots F_n$ for all factor level combination.

H_a: At least one factor and level combination differs from others.

Table 24. ANOVA Table Using Simulated Demand Data

Tests of Between-Subjects Effects	Degress of	Dependent Variable: ME		Dependent Variable: MAD		Dependent Variable: MSE	
Source	freedom	F	Sig.	F	Sig.	F	Sig.
Intercept	1	1488.675624	0.000	39142.07693	0.0000	6234.607107	0.0000
TREATMENT	3	4783.533736	0.000	714.8538978	0.0000	402.6916292	0.0000
REPAIR	1	1628.742157	0.000	20449.7267	0.0000	5927.82539	0.0000
UNIQUE	1	3394.479654	0.000	7503.934454	0.0000	4124.189595	0.0000
DEMAND	1	1987.713576	0.000	19305.5487	0.0000	5925.4271	0.0000
TREATMENT* REPAIR	3	3203.352695	0.000	601.4732241	0.0000	385.6051877	0.0000
TREATMENT * DEMAND	3	1950.806025	0.000	344.2797107	0.0000	390.8696913	0.0000
REPAIR * DEMAND	1	2233.638915	0.000	16660.31382	0.0000	5839.99145	0.0000
TREATMENT * REPAIR * DEMAND	3	1874.80331	0.000	334.9412694	0.0000	387.0477006	0.0000
TREATMENT * UNIQUE	3	923.3884973	0.000	268.7632658	0.0000	211.1630571	0.0000
REPAIR * UNIQUE	1	4055.384292	0.000	6905.726011	0.0000	4081.635679	0.0000
TREATMENT * REPAIR * UNIQUE	3	1150.921029	0.000	292.5884288	0.0000	210.210855	0.0000
UNIQUE * DEMAND	1	2532.718454	0.000	12350.52848	0.0000	4236.196082	0.0000
TREATMENT * UNIQUE * DEMAND	3	1935.874684	0.000	212.1991759	0.0000	219.2808902	0.0000
REPAIR * UNIQUE * DEMAND	1	3470.078219	0.000	11646.55751	0.0000	4187.412727	0.0000
REPAIR * UNIQUE * DEMAND * TREATMENT	3	1654.426832	0.000	151.7985522	0.0000	216.9630555	0.0000
R -Squared / Adjusted R-Squared		0.979	0.978	0.985	0.985	0.964	0.963

The results suggest that at around 0.000 level of significance the H_o should be rejected and it is suspected that at least one treatment mean was not equal on the three parameters representing the forecast error (ME, MAD or MSE).

After suspecting the hypotheses that the treatment means differ, and therefore that the factors somehow affect the mean response, one should determine how the factors affect the mean response. The following test were conducted:

H_o: Factors of repairability, demandability and uniqueness do not interact to affect the response mean

H_a: Factors of repairability, demandability and uniqueness do interact to affect the response mean

The results suggest that at around 0.000 level of significance the H_o should rejected and it is suspected that the factors interact to affect the forecasting error (ME, MAD and MSE).

Because the factors interact, there is difficulty in testing for the main effects. Instead, the treatment means were compared directly in an attempt to learn the nature of their interaction. Rather than compare all 40 pairs of treatment means, the differences between the forecasting methods were studied using a Bonferroni test for each of the parameters of interest (ME, MAD and MSE) [Table 25, Table 26, and Table 27 respectively]. However, these results must be interpreted with caution because the Bonferroni Test shares the same assumptions as ANOVA does.

Table 25. Bonferroni Test for Multiple Comparisons Using the ME

Multiple Comparisons		Dependent Variable: ME			Bonferroni Test	
(I) Forecasting Method	(J) Forecasting Method	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Single Exponential	Double Exp. Brown	9.97*	0.219	0.00000	9.391	10.549
	Moving Average	-0.123	0.219	1.00000	-0.702	0.457
	Autoregression	-15.9575*	0.219	0.00000	-16.537	-15.378
Double Exp. Brown	Single Exponential	-9.97*	0.219	0.00000	-10.549	-9.391
	Moving Average	-10.0925*	0.219	0.00000	-10.672	-9.513
	Autoregression	-25.928	0.219	0.00000	-26.507	-25.348
Moving Average	Single Exponential	0.123	0.219	1.00000	-0.457	0.702
	Double Exp. Brown	10.0925*	0.219	0.00000	9.513	10.672
	Autoregression	-15.835*	0.219	0.00000	-16.414	-15.256
Autoregression	Single Exponential	15.9575*	0.219	0.00000	15.378	16.537
	Double Exp. Brown	25.928	0.219	0.00000	25.348	26.507
	Moving Average	15.835*	0.219	0.00000	15.256	16.414

* The mean difference is significant at the .05 level.

Table 26. Bonferroni Test for Multiple Comparisons Using the MAD

Multiple Comparisons		Dependent Variable: MAD			Bonferroni Test	
					95% Confidence Interval	
(I) Forecasting Method	(J) Forecasting Method	Mean Difference (I-J)	Std. Error	Sig.	Lower Bound	Upper Bound
Single Exponential	Double Exp. Brown	-11.115*	0.286	0.00000	-11.870	-10.361
	Moving Average	0.326	0.286	1.00000	-0.429	1.081
	Autoregression	-5.487*	0.286	0.00000	-6.242	-4.733
Double Exp. Brown	Single Exponential	11.115*	0.286	0.00000	10.361	11.870
	Moving Average	11.441*	0.286	0.00000	10.686	12.196
	Autoregression	5.627*	0.286	0.00000	4.873	6.383
Moving Average	Single Exponential	-0.326	0.286	1.00000	-1.081	0.429
	Double Exp. Brown	-11.441*	0.286	0.00000	-12.196	-10.686
	Autoregression	-5.813*	0.286	0.00000	-6.568	-5.059
Autoregression	Single Exponential	5.487*	0.286	0.00000	4.733	6.242
	Double Exp. Brown	-5.627*	0.286	0.00000	-6.383	-4.873
	Moving Average	5.813*	0.286	0.00000	5.059	6.568

* The mean difference is significant at the .05 level.

Table 27. Bonferroni Test for Multiple Comparisons Using the MSE

Multiple Comparisons		Dependent Variable: MSE			Bonferroni Test	
					95% Confidence Interval	
(I) Forecasting Method	(J) Forecasting Method	Mean Difference (I-J)	Std. Error	Sig.	Lower Bound	Upper Bound
Single Exponential	Double Exp. Brown	-633.248*	24.575	0.00000	-698.166	-568.330
	Moving Average	28.863	24.575	1.00000	-36.055	93.780
	Autoregression	-537.564*	24.575	0.00000	-602.483	-472.647
Double Exp. Brown	Single Exponential	633.248*	24.575	0.00000	568.330	698.166
	Moving Average	662.110*	24.575	0.00000	597.193	727.029
	Autoregression	95.683*	24.575	0.00062	30.765	160.601
Moving Average	Single Exponential	-28.863	24.575	1.00000	-93.780	36.055
	Double Exp. Brown	-662.11*	24.575	0.00000	-727.029	-597.193
	Autoregression	-566.427*	24.575	0.00000	-631.345	-501.510
Autoregression	Single Exponential	537.564*	24.575	0.00000	472.647	602.483
	Double Exp. Brown	-95.683*	24.575	0.00062	-160.601	-30.765
	Moving Average	566.427*	24.575	0.00000	501.510	631.345

* The mean difference is significant at the .05 level.

Observing the Bonferroni test for multiple comparisons, the mean difference of double exponential smoothing and autoregression is significant at the 0.05 level from the mean difference of the moving average and the single exponential smoothing. However, the confidence intervals showed one can not say that single exponential is different from moving average. Based on this information, one should suspect that single exponential and moving average perform better than double exponential and autoregression.

Therefore, the data used for assessing the forecasting performance did not provide enough statistical power to determine the effects during the interactions because the assumptions for normality and equal variances were not met. These results led to performing a non-parametric test.

In spite of the above information, there was not enough information to make reasonable conclusions because of the violations of the assumptions. However, with regard to the validity of the experiment a non-parametric test was required to obtain more statistical validity. The test performed was the "Friedam Test' used in Chapter 3.

Friedman Test Results

The Friedman Tests were conducted on each individual part number based on the information provided by the batch means of the ME, MSE, and MAD. These tests were performed individually to avoid the problems of interaction between the forecasting techniques and the factors and levels combinations. Additionally, if the Friedman Test results in rejection of the null hypothesis an overall test and multiple comparison are performed as previously described in Chapter 3. The results obtained for each individual test are presented in a summary table [Table 28] later in this section.

Concerning the individual tests, the forecast error measures (ME, MAD, MSE) obtained from the application of the four forecasting techniques were introduced in a single table. The procedure to combine the individual measures (ME, MAD, or MSE) were as follows:

- The forecast errors obtained from each forecasting techniques in each batch run were used to calculate the different measures of accuracy (ME, MAD, or MSE)
- The results obtained for each individual measure of accuracy were translated into absolute values.
- The absolute values of each individual measure under the influence of the four forecasting techniques were ranked between each other. The ranking assigns 1 to the individual measure with the absolute value closest to zero, and 4 to the farthest one. In the case of ties, the average of the ranks was used. For example, if the third and fourth ranked measurements tie, rank both (3+4)/2=3.5.
- Combine and compare the ranking of the measures of performance within each part number in a single table using the Friedman Test.

The overall null hypothesis that all forecasting techniques are equal was then tested. Next, multiple rank tests were performed to compare the rank performance between the treatments. For testing the overall null hypothesis the threshold α level of significance selected for the F-test was 0.01. For the multiple rank tests, the threshold α level for the critical T factor was also 0.01. For the purpose of this chapter, the test applied to one part number is displayed in Table 28. The remaining individual calculations are in Appendix H "Final Non-Parametric Test on Simulated Demand Data".

Table 28. Final Non-Parametric Test For Consumable-Low Demand-Specific

Ho:All Forecasting Techniques are equal				**Consumable Low Demand Specific**
b=	150	**$[R(X_{ij})]^2$**	4500	
k=	4	**ΣRj^2**	612346	
K_1=	3	**A_2=**	4500	
K_2=	447	**B_2=**	4082	
T_2=	119 (T statitstics)			
Overall p-value=	**0.010**			
F (α, K_1, K_2)	**3.826** (critical value)			
Reject H_o ?	**Yes** (T_2>F)			

α	$t_{1-0.99/2,1119}$	$T_{critical}$
0.99	2.58688	**43.312**

R> $T_{critical}$; next level

Note: Adapted from Conover, J. 1980: 300

$$|R_{fn-1} - R_f| > t_{1-\alpha/2}\left[\frac{2b(A_2 - B_2)}{(b-1)(k-1)}\right]^{\frac{1}{2}}$$

MULTIPLE COMPARISON

Treat	**Rank**	**I**	**II**
F3	239	A	
F1	292	A	
F2	469		B
F4	500		B

Note: This test include the results obtained in ME, MAD, and MSE for each individual of the 50 replication.

From Table 28 it can be inferred that there was enough evidence with 99% confidence that the forecasting techniques were not equal. It was found that single exponential smoothing and moving average presented better performance than double exponential smoothing and autoregression.

To summarize the results obtained from the Friedman Tests, two summary tables are provided. The first table presents the results of the overall null hypothesis [Table 29]. The second table presents the detailed information about the preferred forecasting technique using the multiple rank tests between the critical factors [Table 30].

Table 29. Non-Parametric Test of the Null Hypothesis

NON-PARAMTERIC TEST- FRIEDMAN			α	0.99
Ho:All Forecasting Techniques are equal			$F(\alpha, K_1, K_2)$	**3.83**
FRIEDMAN TEST			$T_{2=}$	Reject H_o ?
Consumable	Low demand	Specific	118.54	Yes
		Common	447.00	Yes
	High demand	Specific	1377.92	Yes
		Common	300.44	Yes
Repairable	High demand	Common	638.05	Yes
		Specific	18.09	Yes
	Low demand	Common	45.04	Yes
		Specific	17.29	Yes

Looking at the first table [Table 29], it can be said that there was enough evidence (with 99% of confidence) to reject the null hypothesis that all forecasting techniques were equal in every factor combination.

Given that, the null hypothesis for each overall case was rejected. Then, applying the multiple rank tests it was found that single exponential smoothing and moving average are the preferred forecasting methods [Table 30]. For the clarity of Table 30, a forecasting technique ranked with the letter "A" indicates better performance, "B" lower performance and so on. More specifically, Table 30 indicates which forecasting technique is more appropriate for each individual demand category. For example, moving average and single exponential smoothing perform better for consumable-low demand-specific, and so on.

Table 30. Summary of Multiple Rank Test

MULTIPLE RANK TEST				α	0.99	$t_{1-0.99/2,1119}$	2.59
Category	$T_{critical}$	Treat	Rank	I	II	III	IV
Consumable Low demand Specific	43.31	F3	239	A			
		F1	292	A			
		F2	469		B		
		F4	500		B		
Consumable Low demand Common	52.60	F1	278	A			
		F3	339		B		
		F4	425			C	
		F2	458			C	
Consumable High demand Specific	18.13	F3	195	A			
		F1	259		B		
		F4	446			C	
		F2	600				D
Consumable High demand Common	33.42	F1	228	A			
		F3	254	A			
		F4	548		B		
		F2	470			C	
Repairable High demand Common	25.25	F1	209	A			
		F3	244		B		
		F4	489			C	
		F2	558				D
Repairable High demand Specific	54.81	F3	314	A			
		F2	331	A	B		
		F1	405		B	C	
		F4	450			C	
Repairable Low demand Common	50.86	F1	249	A			
		F3	378		B		
		F4	400		B		
		F2	473			C	
Repairable Low demand Specific	54.94	F1	310	A			
		F3	340	A			
		F4	400		B		
		F2	450		B		

Cost Comparison of Current System and Forecasting System

This section presents the results obtained from the analysis of the performance of the different forecasting techniques compared with the current management approach.

The results just presented show that the performance of the forecasting techniques differ, and that single exponential smoothing and moving average performed about the same, but better than double exponential smoothing and autoregression for most parts. Based on this conclusion, the next step was to compare the two available systems to determine if forecasting techniques (either single exponential or moving average) can improve the current planning process of future requirements. Use of the forecasting techniques will be referred to as the "forecasting system", and use of the current planning process will be called the "current system".

In this case, system analysis "assists" decision-makers in choosing preferred future courses of action. This analysis can be done by (1) systematically examining and "reexamining" the relevant objectives and the alternative policies or strategies for achieving them; and (2) comparing quantitatively "where possible" the economic costs, effectiveness (benefits), and risk of alternatives [Fisher, 1974: 6].

The words in quotes in the definition above deserve special comment. The word "assist" is used to emphasize that the purpose of this analysis is to provide a better basis for exercising the judgement of decision-makers through the discovery and outlining of alternatives; the making of comparisons among alternatives [Fisher, 1974: 7].

The word "reexamining" stresses the fact that the original set of alternatives may incomplete and may not even contain those that are most relevant. In other words, additionally alternatives usually have to be generated and investigated [Fisher, 1974: 7].

Finally the words "where possible" suggest that although placing emphasis on the use of quantitative methods is desirable, it does not imply that incisive qualitative analysis is ruled out [Fisher, 1974: 7].

Another important part of the comparison of alternatives is an analysis of the consequences generated by the model. In making such comparison there are two principal approaches [Fisher, 1974: 10]:

1. Fixed effectiveness approach. For a specified level of effectiveness to be attained in the accomplishment of some given objective, the analysis attempt to determine that alternative which is likely to achieve the specified level of effectiveness at the lowest economic cost.
2. Fixed budget approach. For a specified cost level to be used in achieving some given objective, the analysis attempts to determine the alternative that produces the highest effectiveness.

At this point, the analysis between the two systems (forecasting and current) is presented under the assumption of a fixed budget approach. This is because the purpose of the research is to determine if there is any improvement possible within the budget already spent, in terms of costs and benefits, with the forecasting system versus the current system.

For the purpose of this research, cost is defined as the dollar expenditure saved by having a negative difference between the current system and the forecasting system in terms of Net Present Value. This negative difference was calculated using the monthly ending inventory of the two systems. Then, multiply each quantity obtained from the difference by its unit cost and by the corresponding inventory carrying cost. In these cost calculations the inventory carrying cost used is 30% [Melendez, A: 1988: Interview]. Ordering cost is assumed equal for both systems.

Another important consideration in the evaluation of the two alternatives is to measure the benefits obtained for choosing between them. In this particular case, the benefits will be associated with the number of times either of the two systems get a stock-out. Stock-out means that the part was not available in that month, but it was obtained immediately at the beginning of next month. The stock-outs were counted as one (1) if there was unavailable quantity in any period. This stock-out then was measured in percentage per year. In other words, if a part number has stock-outs of 5 items in only one month, it is equivalent to 1 stock-out in 12 periods; then, converted to percentage per year it was equivalent to 1/12=8.3%. This measure of benefits ignores other benefits as time, operational availability, inventory turnover, ordering costs, and devaluation. They were not included in the analysis because in some cases they were assumed equal between the two choices. In other cases the information such as time, operational availability, inventory turnover was not available. In the case of the devaluation of "El peso" (Colombia currency) the unit prices assigned to the items in study corresponded to the last price paid in dollars for the quantity acquired in 1997. Any change in the price caused for the devaluation in that year was already covered for the conservative use of the dollar rate of inflation.

The common factors were the same initial inventory and the replenishment pattern. For the replenishment pattern to be equal, the quantities predicted by the forecasting methods were used as a replenishment pattern observing the same periodicity followed by the current system. For example, if the current system for an item uses a quarterly replenishment, the forecasting system used the same quarterly replenishment policy summing the quantities predicted for that period. In this case, the effect of different replenishment patterns on forecasting accuracy or performance was outside the scope of this study. As a part of the differences, none of them was noted since the idea was to make a fair comparison between the two systems with the information available. It is important to say that additional research on replenishment pattern may be necessary.

The forecasting techniques to be used for the proposed forecasting system were single exponential smoothing or moving average for all factor combinations. Table 31 shows an example of the cost comparison approach for a consumable-low demand-specific item using forecasting data obtained in 1997 from historical demand data in 1996.

Table 31. Individual Calculations of the Cost Difference Between the Systems

Single	Part Category	Part Number	Unit Cost	Starting Inventory (SI)	$Prob_{Stockout}$ Proposal	$Prob_{Stockout}$ Current (Rc)	Total Cost (CP_{NPV})	Carrying cost [r]	Inflation (i)	Reject Ho:
Exponential	CONS-L-S	61-04789	$49.13	30	0.0%	0.0%	$9,147.76	0.3	0.04	Yes
No. Period n	Month	Actual Value Xi	Forecast Value Fi	Replenish Proposal Rp	Ending Inventory Ep=SI-Xi+Rp	Replenish Current Rc	Ending Inventory Ec=SI-Xi+Rc	Purchase Cost CP($)	Differences D Ec-Ep	Cost of Difference D_{NPV}($)
1	Jan	19	4		11		11	0.00	0	0.00
2	Feb	12	13	17	16	20	19	976.18	3	3.47
3	Mar	0	12		16		19	0.00	3	3.46
4	Apr	14	5	17	19	20	25	969.82	6	6.89
5	May	10	10		9		15	0.00	6	6.87
6	Jun	22	10	20	7	20	13	963.50	6	6.85
7	Jul	12	17	17	12	20	21	960.36	9	10.42
8	Aug	16	14	14	10	20	25	957.23	15	17.57
9	Sep	0	15	15	26	20	45	954.10	19	23.19
10	Oct	25	6		1		20	0.00	19	23.11
11	Nov	16	17	23	8	20	24	947.89	16	19.48
12	Dec	1	17	17	24	20	43	944.79	19	22.96
	Sums	147	142	141		160				144.27

As it can be appreciated in this table, the forecasting system performs better than the current management techniques. Using single exponential smoothing there was an absolute savings of $144.27 in an item that had an annual value of $9,147.76 dollars (this value included the purchasing cost plus the value of the initial inventory). Absolute savings of that amount of money may seem very small. However, if this 1.6% savings rate were applied to any other consumable item, the total amount saved could be impressive. Similar calculations were performed for the remaining part numbers and they are presented in Appendix L "Cost Comparison Current System versus the Forecasting System".

For the purpose of the alternative comparison one part number is not conclusive; a summary table [Table 32] including all the costs savings and the probability of stock-out were used to support or reject the null hypothesis.

Table 32. Comparison Between Current and Forecasting Systems

Demand Category	Part Number	Unit Cost ($)	Forecasting Technique	Total cost of CP_{NPV} ($)	Savings Value (NPV) ($)	Savings %	$Prob_{Stockout}$ Current (%)	$Prob_{Stockout}$ Proposed (%)
CONS-L-S	61-04789	49.13	S. expon.	9,147.76	144.27	0.02	0.00	0.00
CONS-L-C	307	1.23	S. expon.	132.08	3.85	0.03	0.00	0.00
CONS-H-S	F1815/WW/RS	17.20	S. expon.	3,341.58	-30.90	-0.01	**0.08**	0.00
CONS-H-C	MS24665-134	0.13	S. expon.	471.75	12.17	0.03	0.00	0.08
REP-H-C	ZP650-SC-M-B-3	1,923.08	S. expon.	212,555.89	10,272.59	0.05	**0.25**	**0.25**
REP-H-S	2-1517	3,762.29	M. Average	604,365.59	72,442.60	0.12	0.00	0.00
REP-L-C	622-2362-001	181.29	S. expon.	11,927.11	1,540.70	0.13	0.00	**0.25**
REP-L-S	DH1030-24-600	1,658.78	M. Average	104,011.90	12,101.27	0.12	0.00	0.00
			Total	**945,953.66**	**96,486.55**	**0.10**	**0.04**	**0.07**

Analyzing the results provided in this summary table, there was only one case (P/N F1815/WW/RS) where the current system performed better than the forecasting system. The remaining seven spare parts showed an improvement in the planning process. In addition, it was very important to note that the absolute amount of savings were $96,486.55 dollars in 8 items that had an annual purchase value of $945,953.66 dollars, which is equivalent to 10.2%.

From this analysis the discussion about the probability of stock-out showed a small advantage for the current system. The customer service level in the current system is 1-4.2%=95.8%, and 1-7.2%= 92.8% with the forecasting system. However, the information about the cost of lost sales for having a stockout is outside of the scope of this study. It can be concluded that setting an appropriate level of safety stock can minimize the effect of the stockout.

Chapter Summary

This chapter discussed the results obtained to answer the research questions. It was found that the performance of the forecasting techniques differ, and that single exponential smoothing and moving average performed about the same, but better than double exponential smoothing and autoregression. Additionally, it can be said that the forecasting system performs better than the current management system. The results illustrated that there was enough evidence to show in 7 out of 8 items that the forecasting system performs better than the current management system. The absolute amount of savings using the forecasting system equated to 10.2% in 8 items that had an annual purchase value of $945,953.66 dollars. The next chapter presents the conclusions and recommendations of the forecasting research.

V. Conclusions and Recommendations

Introduction

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

Research Problem

The CAF recently installed a logistics operating system, EQUALS, to improve communication, reliability, flexibility, and accuracy of the logistics information flowing through the supply channel. However, the initial results showed that the inventory cost and turnover have not stopped growing; subsequently, the operational readiness has been affected by the lead-time within the supply channel. This is a problem because budget allocations require accurate estimates of the product volume to be handled by the logistics system. Under certain circumstances, especially during short term planning such as inventory control, logisticians often find it necessary or useful to produce forecasting information [Ballou, 1992:108-109].

Purpose of this Research

The purpose of the study was twofold. First, this thesis compared several forecasting techniques to be used with consumable and repairable items. The second purpose was to provide a procedure for the Colombian Air Force to plan future aircraft spare parts requirements, based on forecasting techniques, using the information provided by its logistics information system.

Research Questions and Hypotheses

Ballou suggests that the forecasting of demand levels is vital to the firm as a whole as it provides the basic inputs for the planning and control of all functional areas, including logistics, marketing, production and finance [Ballou, 1992: 108-149]. In this case, forecasting is studied as an important aid in effective and efficient planning in the CAF logistics environment. The research questions are as follows:

Research Question No.1. Can forecasting techniques improve the planning process of future requirements for aircraft spare parts with the current information provided by the CAF logistics information system, "EQUALS"? To answer this research question the following hypothesis was tested:

$H1_0$: No performance difference exists between forecasting techniques and current demand management techniques.

$H1_a$: At least one forecasting method is different from current demand management techniques.

Based on the cost comparison results presented in Chapter 4, the hypothesis can be decided. There is enough evidence to say that in 7 out of 8 items the forecasting system performs better than the current management system.

Research Question No.2. What forecasting technique is more appropriate for each demand pattern category? To answer this research questions the following hypothesis was tested:

$H2_o$: No performance differences $F_1 = F_2 \ldots = F_n$ in all demand categories.

$H2_a$: At least one forecasting technique differs from others.

Based on the non-parametric test results (and as suggested by the parametric results) the hypothesis can be decided. There is enough evidence at an α level of 0.01 that at least one forecasting technique was not equal. It was found that the performance of the forecasting techniques differ, and that single exponential smoothing and moving average performed about the same, but better than double exponential smoothing and autoregression.

Results and Management Implication for Research Question No. 1.

Based on the results presented on Chapter 4, the cost difference between the current system and the forecasting system was negative. This negative difference indicates that the replenishment pattern based on the forecasting quantities produced a total absolute savings of $96,486.55 dollars in 8 items that had an annual purchase value of $945,953.66 dollars, which is equivalent to 10.2%. Absolute savings of that amount of money could be very important. If the 10.2% savings apply to all the consumable and repairable items purchased during 1997, the total saved could be even more impressive.

In general, the forecasting system proposed performed better than the current system because it was able to detect the trend and seasonality present in the time series component of the demand data. The findings suggest that the current method is overestimating actual needs.

When demand is stochastic, there is a chance of not being able to satisfy some of the demand on a routine basis directly out of stock. If demand is unusually large, a stock-out may occur or emergency actions may be required to avoid a stockout. On the other hand, if demand is lower than anticipated, the replenishment arrives earlier than needed and excess inventory is carried. In fact, in this study the current system noted that in some cases the demand was underestimated while in other cases it was overestimated.

Managers may have different perspectives on how to balance these two types of risks. There are four possible methods of modeling these management perspectives to arrive at appropriate decision rules. The choice among these should be consistent with the customer's perceptions of what is important. The four methods according to Silver and Pike [1997: 350] are:

1. <u>The Simple Approach</u>, assigning a common safety factor or a common time supply to each item.
2. <u>Safety Stocks Based on Minimizing Costs</u>: These approach involve specifying (explicitly or implicitly) a way of costing a shortage and then minimizing total

cost. The minimization approach trade-off the cost of special transportation versus the cost of holding more inventory.

3. Safety Stocks Based on Customer Service. This approach introduces control parameter known as service level; however the choice in the selection of the service level can increase the cost of holding inventory.

4. Safety Stocks Based on Aggregate Considerations. This approach consists is establishing a safety stock for individual items based on the essentiality of each one.

Safety stock is extra inventory on hand to cushion against stockouts due to fluctuations of demand. It is needed to cover the demand during the replenishment lead time in case actual demand exceeds expected demand, or actual lead time exceed expected lead time. Safety stock has two affects on a firm's cost: it decreases the cost of stockout, and it increases the holding cost. In general, it can be said that safety stocks are needed because forecasts are less than perfect and suppliers sometimes fail to deliver goods on time.

Results and Management Implication for Research Question No. 2

This section summarizes the results obtained from the analysis of which forecasting techniques are more appropriate for each demand pattern and explains the implications that this may have for the Air Force.

Appropriate Forecasting Technique.

The general results obtained from the parametric test (ANOVA) and non-parametric test (Friedman) confirm that simple exponential smoothing and moving average provide more accurate forecasts with 99% confidence than double exponential smoothing and autoregression. Table 33 presents the best forecasting methods for each of the 8 levels of the three factors with their respective parameters.

Table 33. Recommended Forecasting Techniques and Parameters

RECOMMENDED FORECASTING TECHNIQUES			Single Exponential	Parameter α	Moving Average	# periods MA
Consumable	Low demand	Specific	X	0.6	X	5
		Common	X	0.4		
	High demand	Specific			X	5
		Common	X	0.4	X	5
Repairable	High demand	Common	X	0.1		
		Specific	X	0.6	X	8
	Low demand	Common	X	0.1		
		Specific	X	0.3	X	8

Management Implications.

The implementation of a forecasting system may be a long drawn out process whose importance and duration are both often underestimated. Gradual implementation accompanied by extensive education is essential. Where possible, a so-called pilot approach should be first utilized. Specifically, if the new system is adopted it should be implemented on a trial basis on a limited class of items [Silver, 1997: 100].

A prerequisite for effective human involvement in forecasting is transparency in the basic statistical forecasting procedure. Only if the individual understands the assumptions of the underlying model, can he or she apply subjective adjustments to incorporate the effects of other factors not included in the model [Silver, 1997: 123].

Recommendations For Future Studies And Analysis

As discussed in Chapter Four, the forecasting methods did not predict accurately for consumable- high demand-common and specific items. According to Brown [1956: 1], high demand items offer a reliable basis for predicting future demand, which is totally different with the findings of this study. Since only 1 item was used as a representation of the categories in discussion, from a total of 3112 contained in the data, it is important to include more items in the study to obtain a more accurate conclusion about the forecasting performance using single exponential or moving average. Once the results obtained are verified the next step is to apply the forecasting, preferable the same method, to each individual part number. However, to reduce the cost of doing that it is advisable to group the part numbers for class items. This class items classification is outside of the scope of this research. Nevertheless, a good approximation according to Shield [1998: 24] is to forecast the items with high and medium annual demand rate in terms of dollars expenditure, and include deliberately those critical items that are in the lowest expenditure range as high demand because they have a high stock-out cost.

The fact remains that demand for most spare parts cannot now be predicted with confidence, and perhaps never can. This makes it necessary to consider some improvements in logistics operations to make it easier to live with demand uncertainty.

Among such improvements would be a shortening of the resupply time, the procurement lead time, and of the repair cycle for spare parts [Brown1956: viii-xi].

Shortening resupply time would generally reduce the amount of buffer stocks that must be kept at the warehouse. Even though it might cost the system more to reduce resupply time, the savings in required buffer stocks, as well as the reduction in lost performance time for aircraft suffering the shortage, might outweigh this increase in cost [Brown, 1956:ix].

Reducing the procurement lead time, with the option of frequent reorder, would promise considerable economies in the procurement of spare parts. Such shortening in the Air Force might be hard to achieve because it would probably required changes in contractual and procurement techniques. Very likely, reductions in procurement lead time would be accompanied by increases in cost, but these increases should be balanced in the volume of parts procured [Brown, 1956: xi].

A shortening of repair cycle time finally could probably be accomplished by major revisions in the present system of scheduling and doing repair. The ability to repair quickly would permit the system to operate with smaller inventory of parts; and at all stages, it would help to prevent the uncertainty of demand [Brown, 1956: xi].

These improvements would probably have valuable effects in various directions of the organization that lie outside the scope of this research. In relation to the forecasting of demand, they would tend to overcome some of the costly effects of the uncertainty surrounding the predictability of demand for aircraft spare parts.

Conclusions

This research has been concerned with the difficulty of forecasting demand and this remains a very complicated matter because it is very difficult to predict the future with 100% accuracy. Many factors can affect the demand of spare parts, such as economic conditions, political decisions, weather conditions, number of flying hours, number of sorties, mechanics skills, and so on. Each of these variables has their own level of uncertainty. To reduce the level of uncertainty, one forecasting method could be better at one point and another method may perform better at another point of time. Despite the numerous difficulties, there is much that can be done to combat the uncertainty of demand or, at least, to overcome its effects.

According to Silver [1997: 74] forecasts are needed to set up performance standards for customer service, to plan the allocation of total inventory investment, to place replenishment orders, to identify needs for additional production capacity, and to choose between alternative operating strategies. Only one thing is certain after such decisions are made, " the forecasts will be in error". Planning and control procedure should thus reflect the presence of such errors.

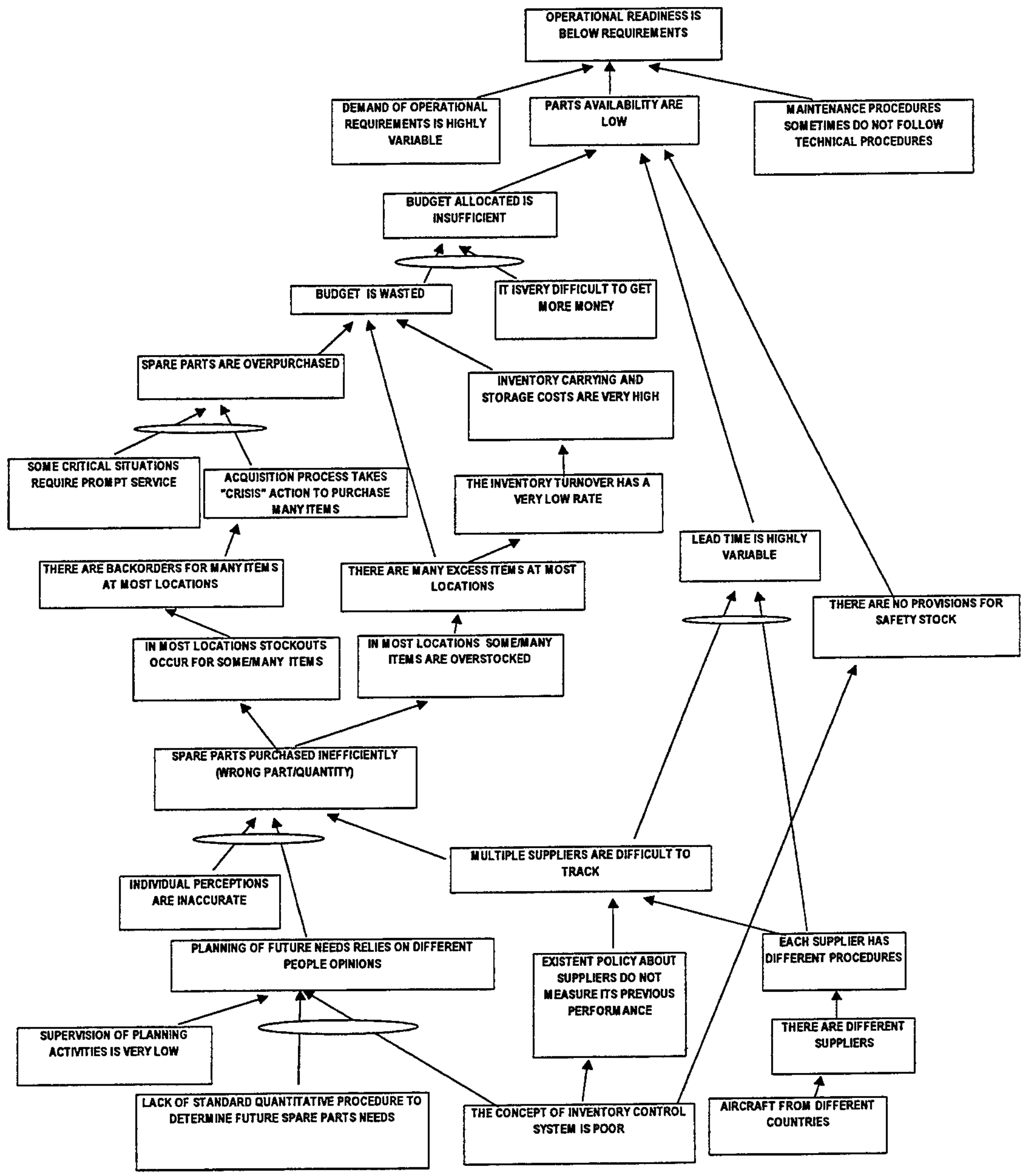
The results of this research demonstrate that in general the forecasting methods perform better than the current management system, and that single exponential smoothing and moving average are more accurate to predict aircraft spare parts demand. It is clear that forecasting method is a useful tool to improve the planning process in an organization.

Since most of the time the forecast is inaccurate, there are additional ways to overcome this difficulty and involve making the logistics system more responsive. These ways could include shortening the resupply time, reducing the procurement lead time, and reducing the cycle time for repair. Such improvements might require major changes in logistics structure and policy; consequently, they would take time to effect. Nevertheless, when all the actions suggested become effective, they will change the Colombian Air Force logistics environment and would improve the budget allocation and operational readiness.

Research Summary

This research presented the problem of improving the planning function by means of using the data provided by its logistics information system. The research consisted of five chapters. The first chapter introduced the purpose of the research and the background surrounding it. The second chapter presented some of the concepts discussed throughout the research. The third chapter illustrated the methodology used for the research. Chapter four provided the results and analysis of the study. Finally, this chapter made some conclusions and recommendations for further studies.

Appendix A: Cause and Effect Diagram



Appendix B: Monthly Demand Of Time Series

	CONSUMABLE				REPAIRABLE			
Quantity No.	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Part Number	61-0478-9	307	F1815/WW/RS	Pin Cotter	ZP650-SC-M-B-3	2-1517	622-2362-001	DH1030-24-600CS
Month	**Low-Specific**	**Low-Common**	**High-Specific**	**High-Common**	**High-Common**	**High-Specific**	**Low-Common**	**Low-Specific**
1	0	25	34	257	5	4	1	0
2	0	2	2	104	2	4	1	2
3	0	2	0	245	2	1	3	0
4	0	0	0	0	0	0	0	0
5	14	3	0	236	1	1	2	0
6	14	4	19	369	3	5	2	0
7	0	0	0	0	0	0	0	0
8	24	17	26	306	8	0	2	0
9	0	18	11	351	11	5	0	0
10	21	7	20	325	9	4	1	6
11	7	6	20	215	8	1	1	1
12	0	9	29	278	16	2	2	0
13	19	0	16	222	17	0	0	0
14	12	0	20	85	8	1	4	0
15	0	2	6	251	0	3	7	1
16	14	2	17	257	3	2	1	0
17	10	0	10	328	1	4	0	1
18	22	2	30	284	4	3	0	5
19	12	1	22	322	6	3	0	0
20	16	0	7	42	2	1	0	2
21	0	3	20	337	0	6	1	0
22	25	0	26	326	9	3	1	0
23	16	0	13	146	8	3	1	0
24	1	2	17	336	7	5	0	3
Grand Total	227	105	365	5622	94	61	30	21

Appendix C: Forecasting Calculations for 1997 Using Historical Demand Data

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty1	CONS-L-S	61-04789	Battery Ni-Cad	alpha=0.6	Exponential	$49.13
Month to be Forecasted	No. Period n	Actual Value XI	Forecast Value FI	Error EI= XI - FI	(Error)2 E2	APE (100)*(|EI| / XI)
Jan	1	19	4	15	221.63	78.35
Feb	2	12	13	-1	1.09	8.71
Mar	3	0	12	-12	154.21	#DIV/0!
Apr	4	14	5	9	81.59	64.52
May	5	10	10	0	0.15	3.87
Jun	6	22	10	12	140.31	53.84
Jul	7	12	17	-5	27.69	43.85
Aug	8	16	14	2	3.59	11.85
Sep	9	0	15	-15	232.32	#DIV/0!
Oct	10	25	6	19	357.33	75.61
Nov	11	16	17	-1	2.07	8.99
Dec	12	1	17	-16	242.60	1557.55
Sums		147	142	5	1464.57	#DIV/0!
Measures of Accuracy						
CFE	ME	MAD	MSE	SE	MAPE	
5	0.43	9	122.05	11.54	#DIV/0!	

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty1	CONS-L-S	61-04789	Battery Ni-Cad	alpha=0.1	D.Exponential	$49.13
Month to be Forecasted	No. Period n	Actual Value XI	Forecast Value FI	Error EI= XI - FI	(Error)2 E2	APE (100)*(|EI| / XI)
Jan	1	19	9	10	110.06	55.22
Feb	2	12	11	1	1.12	8.82
Mar	3	0	12	-12	134.20	#DIV/0!
Apr	4	14	10	4	18.52	30.74
May	5	10	11	-1	0.78	8.85
Jun	6	22	11	11	119.36	49.66
Jul	7	12	14	-2	2.66	13.59
Aug	8	16	14	2	4.95	13.91
Sep	9	0	15	-15	215.42	#DIV/0!
Oct	10	25	12	13	163.74	51.18
Nov	11	16	15	1	0.80	5.59
Dec	12	1	16	-15	217.44	1474.60
Sums		147	148	-1	989.06	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
-1	0.07	7	82.42	9.48	#DIV/0!	

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 2	CONS-L-C	307	Light	alpha=0.4	Exponential	$1.23
Month to be Forecasted	No. Period n	Actual Value XI	Forecast Value FI	Error EI= XI - FI	(Error)2 E2	APE (100)*(|EI| / XI)
Jan	1	0	9	-9	74.06	#DIV/0!
Feb	2	0	5	-5	26.66	#DIV/0!
Mar	3	2	3	-1	1.21	54.90
Apr	4	2	3	-1	0.43	32.94
May	5	0	2	-2	5.74	#DIV/0!
Jun	6	2	1	1	0.32	28.14
Jul	7	1	2	-1	0.44	66.23
Aug	8	0	1	-1	1.95	#DIV/0!
Sep	9	3	1	2	4.67	72.05
Oct	10	0	2	-2	2.90	#DIV/0!
Nov	11	0	1	-1	1.04	#DIV/0!
Dec	12	2	1	1	1.92	69.34
Sums		12	31	-19	121.34	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
-19	1.55	2	10.11	3.32	#DIV/0!	

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 2	CONS-L-C	307	Light	alpha=0.4	D.Exponential	$1.23
Month to be Forecasted	No. Period n	Actual Value XI	Forecast Value FI	Error EI= XI - FI	(Error)2 E2	APE (100)*(|EI| / XI)
Jan	1	0	9	-9	80.86	#DIV/0!
Feb	2	0	1	-1	1.07	#DIV/0!
Mar	3	2	-2	4	15.96	199.75
Apr	4	2	-1	3	8.72	147.67
May	5	0	0	0	0.01	#DIV/0!
Jun	6	2	-1	3	10.74	163.86
Jul	7	1	0	1	0.46	68.11
Aug	8	0	0	0	0.07	#DIV/0!
Sep	9	3	-1	4	12.63	118.48
Oct	10	0	2	-2	3.85	#DIV/0!
Nov	11	0	0	0	0.10	#DIV/0!
Dec	12	2	0	2	5.42	116.45
Sums		12	8	4	139.90	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
4	0.36	2	11.66	3.57	#DIV/0!	

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 3	CONS-H-S	F1815/WW/RS	Bulb Lamp	alpha=0.3	Exponential	$17.20
Month to be Forecasted	No. Period n	Actual Value XI	Forecast Value FI	Error EI= XI - FI	(Error)2 E2	APE (100)*(|EI| / XI)
Jan	1	16	20	-4	12.48	22.08
Feb	2	20	18	2	2.33	7.64
Mar	3	6	19	-13	167.21	215.51
Apr	4	17	15	2	3.80	11.46
May	5	10	16	-6	31.77	56.36
Jun	6	30	14	16	257.75	53.52
Jul	7	22	19	3	10.49	14.72
Aug	8	7	20	-13	162.13	181.90
Sep	9	20	16	4	16.70	20.43
Oct	10	26	17	9	78.51	34.08
Nov	11	13	20	-7	46.21	52.29
Dec	12	17	18	-1	0.57	4.46
Sums		204	211	-7	789.95	674.4
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
-7	0.56	7	65.83	8.47	56.20	

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 3	CONS-H-S	F1815/WW/RS	Bulb Lamp	alpha=0.8	D.Exponential	$17.20
Month to be Forecasted	No. Period n	Actual Value XI	Forecast Value FI	Error EI= XI - FI	(Error)2 E2	APE (100)*(|EI| / XI)
Jan	1	16	60	-44	1936.49	275.03
Feb	2	20	-13	33	1065.69	163.22
Mar	3	6	19	-13	180.14	223.70
Apr	4	17	-37	54	2933.90	318.62
May	5	10	34	-24	573.93	239.57
Jun	6	30	-3	33	1100.29	110.57
Jul	7	22	87	-65	4221.55	295.33
Aug	8	7	21	-14	191.44	197.66
Sep	9	20	-43	63	4027.74	317.32
Oct	10	26	40	-14	205.66	55.16
Nov	11	13	56	-43	1817.73	327.96
Dec	12	17	-17	34	1142.42	198.82
Sums		204	204	0	19396.99	2723.0
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
0	0.01	36	1616.42	41.99	226.91	

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 4	CONS-H-C	MS24665-134	Cotter Pin	alpha=0.4	Exponential	$0.14
Month to be Forecasted	No. Period n	Actual Value XI	Forecast Value FI	Error EI= XI - FI	(Error)2 E2	APE (100)*(|EI| / XI)
Jan	1	222	267	-45	1985.38	20.07
Feb	2	85	249	-164	26809.01	192.63
Mar	3	251	183	68	4591.32	27.00
Apr	4	257	210	47	2176.74	18.15
May	5	328	229	99	9799.68	30.18
Jun	6	284	269	15	237.04	5.42
Jul	7	322	275	47	2231.39	14.67
Aug	8	42	294	-252	63331.47	599.18
Sep	9	337	193	144	20737.59	42.73
Oct	10	326	251	75	5685.66	23.13
Nov	11	146	281	-135	18159.72	92.30
Dec	12	336	227	109	11912.67	32.48
Sums		2936	2926	10	167657.67	1098.0
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
10	0.82	100	13971.47	123.46	91.50	

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 4	CONS-H-C	MS24665-134	Cotter Pin	alpha=0.4	D.Exponential	$187.31
Month to be Forecasted	No. Period n	Actual Value XI	Forecast Value FI	Error EI= XI - FI	(Error)2 E2	APE (100)*(|EI| / XI)
Jan	1	222	291	-69	4765.60	31.10
Feb	2	85	241	-156	24287.40	183.35
Mar	3	251	96	155	24165.44	61.93
Apr	4	257	192	65	4217.21	25.27
May	5	328	242	86	7452.04	26.32
Jun	6	284	326	-42	1794.50	14.92
Jul	7	322	317	5	22.87	1.49
Aug	8	42	343	-301	90639.68	716.82
Sep	9	337	95	242	58500.08	71.77
Oct	10	326	265	61	3740.29	18.76
Nov	11	146	328	-182	32945.73	124.32
Dec	12	336	187	149	22311.89	44.46
Sums		2936	2922	14	274842.72	1320.5
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
14	1.17	126	22903.56	158.07	110.04	

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 5	REP-H-C	ZP650-SC-M-B-3	Oxigen Bottle	alpha=0.1	Exponential	$1,923.08
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	17	5	12	150.55	72.17
Feb	2	8	6	2	4.17	25.53
Mar	3	0	6	-6	37.96	#DIV/0!
Apr	4	3	6	-3	6.48	84.85
May	5	1	5	-4	18.41	429.08
Jun	6	4	5	-1	0.74	21.54
Jul	7	6	5	1	1.50	20.41
Aug	8	2	5	-3	8.40	144.90
Sep	9	0	5	-5	21.24	#DIV/0!
Oct	10	9	4	5	23.55	53.92
Nov	11	8	5	3	11.34	42.09
Dec	12	7	5	2	4.12	29.01
Sums		65	61	4	288.46	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
4	0.37	4	24.04	5.12	#DIV/0!	

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 5	REP-H-C	ZP650-SC-M	Oxigen Bottle	alpha=0.6	D.Exponential	$1,923.08
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	17	22	-5	24.54	29.14
Feb	2	8	24	-16	243.74	195.15
Mar	3	0	6	-6	34.07	#DIV/0!
Apr	4	3	-10	13	172.88	438.28
May	5	1	-4	5	23.35	483.25
Jun	6	4	-4	8	61.50	196.06
Jul	7	6	3	3	8.30	48.01
Aug	8	2	8	-6	36.36	301.51
Sep	9	0	1	-1	1.27	#DIV/0!
Oct	10	9	-3	12	147.50	134.94
Nov	11	8	13	-5	24.64	62.05
Dec	12	7	12	-5	28.89	76.78
Sums		65	68	-3	807.04	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
-3	0.25	7	67.25	8.57	#DIV/0!	

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 6	REP-H-S	2-1517	Brake Assy	alpha=0.5	Exponential	$3,762.29
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	0	2	-2	4.45	#DIV/0!
Feb	2	1	1	0	0.00	5.42
Mar	3	3	1	2	3.89	65.76
Apr	4	2	2	0	0.00	0.68
May	5	4	2	2	3.97	49.83
Jun	6	3	3	0	0.00	0.11
Jul	7	3	3	0	0.00	0.06
Aug	8	1	3	-2	4.00	200.08
Sep	9	6	2	4	16.00	66.66
Oct	10	3	4	-1	1.00	33.34
Nov	11	3	4	-1	0.25	16.67
Dec	12	5	3	2	3.06	35.00
Sums		34	30	4	36.63	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
4	0.34	1	3.05	1.82	#DIV/0!	

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 6	REP-H-S	2-1517	Brake Assy	alpha=0.7	D.Exponential	$3,762.29
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	0	1	-1	0.79	#DIV/0!
Feb	2	1	-3	4	18.88	434.54
Mar	3	3	0	3	6.47	84.79
Apr	4	2	6	-4	17.23	207.58
May	5	4	3	1	2.03	35.59
Jun	6	3	7	-4	16.47	135.30
Jul	7	3	3	0	0.18	14.00
Aug	8	1	3	-2	3.56	188.68
Sep	9	6	-2	8	67.12	136.54
Oct	10	3	12	-9	74.50	287.71
Nov	11	3	2	1	0.26	17.13
Dec	12	5	2	3	9.52	61.70
Sums		34	34	0	217.01	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
0	0.01	3	18.08	4.44	#DIV/0!	

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 7	REP-L-C	622-2362-001	Receiver ADF	alpha=0.1	Exponential	$181.29
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	0	1	-1	0.73	#DIV/0!
Feb	2	4	1	3	10.43	80.76
Mar	3	7	1	6	34.90	84.39
Apr	4	1	2	-1	0.47	68.35
May	5	0	2	-2	2.61	#DIV/0!
Jun	6	0	1	-1	2.11	#DIV/0!
Jul	7	0	1	-1	1.71	#DIV/0!
Aug	8	0	1	-1	1.39	#DIV/0!
Sep	9	1	1	0	0.00	5.97
Oct	10	1	1	0	0.00	5.37
Nov	11	1	1	0	0.00	4.84
Dec	12	0	1	-1	1.09	#DIV/0!
Sums		15	14	1	55.45	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
1	0.07	1	4.62	2.25	#DIV/0!	

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 7	REP-L-C	622-2362-001	Receiver ADF	alpha=0.5	D.Exponential	$181.29
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	0	2	-2	5.14	#DIV/0!
Feb	2	4	0	4	15.72	99.13
Mar	3	7	4	3	6.41	36.17
Apr	4	1	9	-8	67.40	820.96
May	5	0	2	-2	5.49	#DIV/0!
Jun	6	0	-1	1	0.92	#DIV/0!
Jul	7	0	-2	2	2.39	#DIV/0!
Aug	8	0	-1	1	1.70	#DIV/0!
Sep	9	1	-1	2	3.68	191.92
Oct	10	1	1	0	0.12	34.28
Nov	11	1	1	0	0.02	13.70
Dec	12	0	1	-1	1.50	#DIV/0!
Sums		15	17	-2	110.48	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
-2	0.13	2	9.21	3.17	#DIV/0!	

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 8	REP-L-S	DH1030-24-600	Inverter	alpha=0.3	Exponential	$1,658.78
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	0	1	-1	1.23	#DIV/0!
Feb	2	0	1	-1	0.60	#DIV/0!
Mar	3	1	1	0	0.21	45.66
Apr	4	0	1	-1	0.46	#DIV/0!
May	5	1	0	1	0.27	52.37
Jun	6	5	1	4	19.07	87.33
Jul	7	0	2	-2	3.78	#DIV/0!
Aug	8	2	1	1	0.41	31.98
Sep	9	0	2	-2	2.41	#DIV/0!
Oct	10	0	1	-1	1.18	#DIV/0!
Nov	11	0	1	-1	0.58	#DIV/0!
Dec	12	3	1	2	6.09	82.25
Sums		12	11	1	36.29	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
1	0.05	1	3.02	1.82	#DIV/0!	

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 8	REP-L-S	DH1030-24-600	Inverter	alpha=0.3	D.Exponential	$1,658.78
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	0	1	-1	1.75	#DIV/0!
Feb	2	0	1	-1	0.30	#DIV/0!
Mar	3	1	0	1	0.77	87.70
Apr	4	0	1	-1	0.29	#DIV/0!
May	5	1	0	1	0.73	85.19
Jun	6	5	1	4	19.53	88.38
Jul	7	0	3	-3	11.46	#DIV/0!
Aug	8	2	2	0	0.08	14.42
Sep	9	0	2	-2	4.06	#DIV/0!
Oct	10	0	1	-1	0.78	#DIV/0!
Nov	11	0	0	0	0.06	#DIV/0!
Dec	12	3	0	3	9.50	102.72
Sums		12	11	1	49.31	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
1	0.05	2	4.11	2.12	#DIV/0!	

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty1	CONS-L-S	61-04789	Battery Ni-Cad	5	M. Average	$49.13
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	19	10	9	73.96	45.26
Feb	2	12	9	3	6.76	21.67
Mar	3	0	12	-12	139.24	#DIV/0!
Apr	4	14	8	6	40.96	45.71
May	5	10	9	1	1.00	10.00
Jun	6	22	11	11	121.00	50.00
Jul	7	12	12	0	0.16	3.33
Aug	8	16	12	4	19.36	27.50
Sep	9	0	15	-15	219.04	#DIV/0!
Oct	10	25	12	13	169.00	52.00
Nov	11	16	15	1	1.00	6.25
Dec	12	1	14	-13	163.84	1280.00
Sums		147	138	9	955.32	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
9	0.75	7	79.61	9.32	#DIV/0!	

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty1	CONS-L-S	61-04789	Battery Ni-Cad	3 lags	Autoregression	$49.13
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	19	23	-4	12.33	18.48
Feb	2	12	2	10	109.08	87.03
Mar	3	0	5	-5	25.48	#DIV/0!
Apr	4	14	22	-8	65.06	57.61
May	5	10	8	2	6.15	24.79
Jun	6	22	6	16	259.24	73.19
Jul	7	12	4	8	63.73	66.53
Aug	8	16	10	6	32.21	35.47
Sep	9	0	12	-12	153.34	#DIV/0!
Oct	10	25	19	6	35.56	23.85
Nov	11	16	2	14	200.99	88.61
Dec	12	1	3	-2	3.65	191.00
Sums		147	115	32	966.80	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
32	2.66	8	80.57	9.38	#DIV/0!	
			β_0	$\beta\tau_{-1}$	$\beta\tau_{-2}$	$\beta\tau_{-3}$
			11.353	-0.698	0.109	0.495

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 2	CONS-L-C	307	Light	5	M. Average	$1.23
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	0	11	-11	129.96	#DIV/0!
Feb	2	0	8	-8	64.00	#DIV/0!
Mar	3	2	4	-2	5.76	120.00
Apr	4	2	3	-1	1.96	70.00
May	5	0	3	-3	6.76	#DIV/0!
Jun	6	2	1	1	1.44	60.00
Jul	7	1	1	0	0.04	20.00
Aug	8	0	1	-1	1.96	#DIV/0!
Sep	9	3	1	2	4.00	66.67
Oct	10	0	1	-1	1.44	#DIV/0!
Nov	11	0	1	-1	1.44	#DIV/0!
Dec	12	2	1	1	1.44	60.00
Sums		12	37	-25	220.20	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
-25	2.12	3	18.35	4.47	#DIV/0!	

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 2	CONS-L-C	307	Light	1 lag	Autoregression	$1.23
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	0	8	-8	65.50	#DIV/0!
Feb	2	0	5	-5	22.86	#DIV/0!
Mar	3	2	5	-3	7.73	139.05
Apr	4	2	6	-4	12.37	175.85
May	5	0	6	-6	30.44	#DIV/0!
Jun	6	2	5	-3	7.73	139.05
Jul	7	1	6	-5	20.40	451.70
Aug	8	0	5	-5	26.51	#DIV/0!
Sep	9	3	5	-2	3.17	59.37
Oct	10	0	6	-6	34.63	#DIV/0!
Nov	11	0	5	-5	22.86	#DIV/0!
Dec	12	2	5	-3	7.73	139.05
Sums		12	64	-52	261.94	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
-52	4.36	4	21.83	4.88	#DIV/0!	
			β_0	$\beta\tau_{-1}$	$\beta\tau_{-2}$	$\beta\tau_{-3}$
			4.781	0.368		

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 3	CONS-H-S	F1815/WW/RS	Bulb Lamp	9	M. Average	$17.20
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	16	14	2	4.46	13.19
Feb	2	20	16	4	18.78	21.67
Mar	3	6	18	-12	141.35	198.15
Apr	4	17	16	1	0.31	3.27
May	5	10	18	-8	69.44	83.33
Jun	6	30	17	13	180.75	44.81
Jul	7	22	19	3	11.11	15.15
Aug	8	7	19	-12	141.35	169.84
Sep	9	20	17	3	6.53	12.78
Oct	10	26	16	10	91.31	36.75
Nov	11	13	18	-5	20.75	35.04
Dec	12	17	17	0	0.05	1.31
Sums		204	205	-1	686.19	635.3
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
-1	0.05	6	57.18	7.90	52.94	

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 3	CONS-H-S	F1815/WW/RS	Bulb Lamp	2 lags	Autoregression	$17.20
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	16	23	-7	52.45	45.26
Feb	2	20	31	-11	113.78	53.34
Mar	3	6	20	-14	194.38	232.37
Apr	4	17	23	-6	38.96	36.72
May	5	10	12	-2	2.86	16.92
Jun	6	30	21	9	85.25	30.78
Jul	7	22	15	7	49.11	31.85
Aug	8	7	31	-24	599.86	349.89
Sep	9	20	25	-5	23.93	24.46
Oct	10	26	13	13	181.79	51.86
Nov	11	13	23	-10	104.90	78.78
Dec	12	17	28	-11	125.26	65.84
Sums		204	265	-61	1572.54	1018.1
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
-61	5.07	10	131.04	11.96	84.84	
			β_0	$\beta\tau_{-2}$	$\beta\tau_{-1}$	$\beta\tau_{-3}$
			6.742	0.825		

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 4	CONS-H-C	MS24665-134	Cotter Pin	9	M. Average	$187.31
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	222	231	-9	83.01	4.10
Feb	2	85	256	-171	29165.05	200.92
Mar	3	251	239	12	144.00	4.78
Apr	4	257	226	31	967.90	12.11
May	5	328	254	74	5410.42	22.43
Jun	6	284	257	27	735.01	9.55
Jul	7	322	249	73	5264.31	22.53
Aug	8	42	249	-207	42895.01	493.12
Sep	9	337	230	107	11472.79	31.78
Oct	10	326	236	90	8020.20	27.47
Nov	11	146	248	-102	10404.00	69.86
Dec	12	336	255	81	6597.05	24.17
Sums		2936	2931	5	121158.75	922.8
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
5	0.44	82	10096.56	104.95	76.90	

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 4	CONS-H-C	MS24665-134	Cotter Pin	1	Autoregression	$187.31
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	222	267	-45	2026.08	20.28
Feb	2	85	233	-148	22008.32	174.53
Mar	3	251	253	-2	2.66	0.65
Apr	4	257	235	22	462.51	8.37
May	5	328	194	134	18070.89	40.98
Jun	6	284	244	40	1570.70	13.95
Jul	7	322	246	76	5745.03	23.54
Aug	8	42	268	-226	51044.36	537.93
Sep	9	337	254	83	6811.86	24.49
Oct	10	326	266	60	3588.73	18.38
Nov	11	146	180	-34	1184.32	23.57
Dec	12	336	271	65	4266.18	19.44
Sums		2936	2912	24	116781.64	906.1
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
24	1.98	78	9731.80	103.04	75.51	
			β_0	$\beta\tau_{-3}$	$\beta\tau_{-1}$	$\beta\tau_{-2}$
			167.562	0.306		

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 5	REP-H-C	ZP650-SC-M-B-3	Oxigen Bottle	8	M. Average	$1,923.08
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	17	6	11	116.16	63.40
Feb	2	8	8	0	0.00	0.00
Mar	3	0	9	-9	73.20	#DIV/0!
Apr	4	3	9	-6	30.86	185.19
May	5	1	8	-7	49.00	700.00
Jun	6	4	7	-3	8.35	72.22
Jul	7	6	6	0	0.11	5.56
Aug	8	2	6	-4	16.90	205.56
Sep	9	0	5	-5	20.75	#DIV/0!
Oct	10	9	3	6	40.11	70.37
Nov	11	8	3	5	27.27	65.28
Dec	12	7	4	3	11.11	47.62
Sums		65	72	-7	393.83	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
-7	0.61	5	32.82	5.98	#DIV/0!	

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 5	REP-H-C	ZP650-SC-M-B-3	Oxigen Bottle	1 lag	Autoregression	$1,923.08
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	17	16	1	0.87	5.48
Feb	2	8	17	-9	79.89	111.73
Mar	3	0	9	-9	83.12	#DIV/0!
Apr	4	3	2	1	0.70	27.83
May	5	1	5	-4	14.23	377.20
Jun	6	4	3	1	0.93	24.15
Jul	7	6	6	0	0.13	5.98
Aug	8	2	7	-5	28.93	268.95
Sep	9	0	4	-4	15.23	#DIV/0!
Oct	10	9	2	7	46.72	75.94
Nov	11	8	10	-2	3.94	24.83
Dec	12	7	9	-2	4.48	30.24
Sums		65	90	-25	279.17	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
-25	2.11	4	23.26	5.04	#DIV/0!	
			β_0	$\beta\tau_{-1}$	$\beta\tau_{-2}$	$\beta\tau_{-3}$
			2.165	0.869		

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 6	REP-H-S	2-1517	Brake Assy	8	M. Average	$3,762.29
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	0	2	-2	5.06	#DIV/0!
Feb	2	1	2	-1	1.27	112.50
Mar	3	3	2	1	1.89	45.83
Apr	4	2	2	0	0.00	0.00
May	5	4	2	2	3.06	43.75
Jun	6	3	2	1	0.77	29.17
Jul	7	3	2	1	1.00	33.33
Aug	8	1	2	-1	1.56	125.00
Sep	9	6	2	4	15.02	64.58
Oct	10	3	3	0	0.02	4.17
Nov	11	3	3	0	0.02	4.17
Dec	12	5	3	2	3.52	37.50
Sums		34	28	6	33.17	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
6	0.51	1	2.76	1.74	#DIV/0!	

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 6	REP-H-S	2-1517	Brake Assy	1 lag	Autoregression	$3,762.29
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	0.0	2.8	-3	7.86	#DIV/0!
Feb	2	1	2.1	-1	1.32	114.70
Mar	3	3	3.5	0	0.21	15.37
Apr	4	2	2.8	-1	0.65	40.20
May	5	4	1.5	3	6.30	62.75
Jun	6	3	2.1	1	0.73	28.43
Jul	7	3	0.8	2	4.70	72.23
Aug	8	1	1.5	0	0.24	49.00
Sep	9	6	1.5	5	20.34	75.17
Oct	10	3	2.8	0	0.04	6.53
Nov	11	3	0.0	3	9.00	100.00
Dec	12	5	1.5	4	12.32	70.20
Sums		34	23	11	63.70	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
11	0.92	2	5.31	2.41	#DIV/0!	
			β_0	$\beta\tau_{-2}$	$\beta\tau_{-1}$	$\beta\tau_{-3}$
			3.461	-0.657		

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 7	REP-L-C	622-2362-001	Receiver ADF	9	M. Average	$181.29
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	0	1	-1	1.23	#DIV/0!
Feb	2	4	1	3	8.35	72.22
Mar	3	7	1	6	32.11	80.95
Apr	4	1	2	-1	0.79	88.89
May	5	0	2	-2	4.00	#DIV/0!
Jun	6	0	2	-2	3.16	#DIV/0!
Jul	7	0	2	-2	3.16	#DIV/0!
Aug	8	0	2	-2	2.78	#DIV/0!
Sep	9	1	2	-1	0.31	55.56
Oct	10	1	1	0	0.20	44.44
Nov	11	1	2	-1	0.31	55.56
Dec	12	0	0	0	0.20	#DIV/0!
Sums		15	18	-3	56.59	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
-3	0.22	2	4.72	2.27	#DIV/0!	

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 7	REP-L-C	622-2362-001	Receiver ADF	2 lag	Autoregression	$181.29
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	0	1	-1	0.35	#DIV/0!
Feb	2	4	2	2	4.96	55.68
Mar	3	7	0	7	53.47	104.46
Apr	4	1	-3	4	13.35	365.40
May	5	0	2	-2	4.12	#DIV/0!
Jun	6	0	3	-3	12.05	#DIV/0!
Jul	7	0	2	-2	3.14	#DIV/0!
Aug	8	0	1	-1	2.22	#DIV/0!
Sep	9	1	1	0	0.24	49.00
Oct	10	1	1	0	0.01	10.20
Nov	11	1	1	0	0.01	10.20
Dec	12	0	1	-1	1.39	#DIV/0!
Sums		15	13	2	95.31	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
2	0.20	2	7.94	2.94	#DIV/0!	
			β_0	$\beta\tau_{-1}$	$\beta\tau_{-2}$	$\beta\tau_{-3}$
			1.49	-0.592		0.283

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 8	REP-L-S	DH1030-24-600	Inverter	8	M. Average	$1,658.78
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	0	1	-1	0.77	
Feb	2	0	1	-1	0.77	#DIV/0!
Mar	3	1	1	0	0.02	12.50
Apr	4	0	1	-1	1.00	#DIV/0!
May	5	1	1	0	0.00	0.00
Jun	6	5	1	4	15.02	77.50
Jul	7	0	1	-1	1.00	#DIV/0!
Aug	8	2	1	1	1.27	56.25
Sep	9	0	1	-1	1.27	#DIV/0!
Oct	10	0	1	-1	1.27	#DIV/0!
Nov	11	0	1	-1	1.27	#DIV/0!
Dec	12	3	1	2	4.00	66.67
Sums		12	12	0	27.63	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
0	0.00	1	2.30	1.58	#DIV/0!	

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 8	REP-L-S	DH1030-24-600	Inverter	1 lag	Autoregression	$1,658.78
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	0	1	-1	0.57	#DIV/0!
Feb	2	0	1	-1	0.89	#DIV/0!
Mar	3	1	1	0	0.00	5.40
Apr	4	0	1	-1	0.89	#DIV/0!
May	5	1	1	0	0.06	24.30
Jun	6	5	1	4	16.43	81.08
Jul	7	0	1	-1	0.57	#DIV/0!
Aug	8	2	0	2	4.00	99.95
Sep	9	0	1	-1	0.89	#DIV/0!
Oct	10	0	1	-1	0.32	#DIV/0!
Nov	11	0	1	-1	0.89	#DIV/0!
Dec	12	3	1	2	4.22	68.47
Sums		12	9	3	29.76	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
3	0.21	1	2.48	1.64	#DIV/0!	
			β_0	$\beta\tau_{-2}$	$\beta\tau_{-3}$	$\beta\tau_{-1}$
			0.946	-0.189		

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty1	CONS-L-S	61-04789	Battery Ni-Cad	1	Linear Regression	$49.13
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	19	2	17	278.22	87.79
Feb	2	12	3	9	79.03	74.08
Mar	3	0	4	-4	15.21	#DIV/0!
Apr	4	14	5	9	86.68	66.50
May	5	10	5	5	20.43	45.20
Jun	6	22	6	16	247.43	71.50
Jul	7	12	7	5	24.40	41.17
Aug	8	16	8	8	66.42	50.94
Sep	9	0	9	-9	74.65	#DIV/0!
Oct	10	25	9	16	242.42	62.28
Nov	11	16	10	6	33.41	36.13
Dec	12	1	11	-10	100.20	1001.00
Sums		147	80	67	1268.51	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
67	5.59	9	105.71	10.74	#DIV/0!	
			β_0	β_{tmonth}	β_{thour}	β_{tcycle}
			1.530	0.79		

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 2	CONS-L-C	307	Light	1	Linear Regression	$1.23
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	0	7	-7	53.40	#DIV/0!
Feb	2	0	7	-7	54.58	#DIV/0!
Mar	3	2	7	-5	29.90	273.41
Apr	4	2	8	-6	30.79	277.43
May	5	0	8	-8	58.20	#DIV/0!
Jun	6	2	8	-6	32.60	285.47
Jul	7	1	8	-7	46.10	678.98
Aug	8	0	8	-8	61.94	#DIV/0!
Sep	9	3	8	-5	24.51	165.02
Oct	10	0	8	-8	64.50	#DIV/0!
Nov	11	0	8	-8	65.79	#DIV/0!
Dec	12	2	8	-6	38.34	309.59
Sums		12	93	-81	560.64	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
-81	6.75	7	46.72	7.14	#DIV/0!	
			β_0	β_{tmonth}	β_{thour}	β_{tcycle}
			7.227	0.0804		

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 3	CONS-H-S	F1615/WW/RS	Bulb Lamp	3	Linear Regression	$17.20
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	16	-8	24	594.73	152.42
Feb	2	20	-2	22	480.87	109.64
Mar	3	6	0	6	35.09	98.73
Apr	4	17	0	17	275.07	97.56
May	5	10	11	-1	1.83	13.54
Jun	6	30	17	13	165.99	42.95
Jul	7	22	9	13	175.56	60.23
Aug	8	7	18	-11	120.02	156.50
Sep	9	20	27	-7	46.97	34.27
Oct	10	26	27	-1	0.40	2.44
Nov	11	13	35	-22	499.94	171.99
Dec	12	17	38	-21	449.87	124.76
Sums		204	172	32	2846.34	1065.0
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
32	2.63	13	237.20	16.09	88.75	
			β_0	β_{tmonth}	β_{thour}	β_{tcycle}
			54.719	3.043	-0.334	0.147

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 4	CONS-H-C	MS24665-134	Cotter Pin	1	Linear Regression	$187.31
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	222	159	63	4004.61	28.51
Feb	2	85	171	-86	7320.00	100.66
Mar	3	251	182	69	4706.51	27.33
Apr	4	257	194	63	3939.45	24.42
May	5	328	206	122	14865.95	37.17
Jun	6	284	218	66	4367.49	23.27
Jul	7	322	230	92	8509.69	28.65
Aug	8	42	242	-200	39836.57	475.22
Sep	9	337	253	84	6983.94	24.80
Oct	10	326	265	61	3688.25	18.63
Nov	11	146	277	-131	17189.31	89.80
Dec	12	336	289	47	2213.98	14.00
Sums		2936	2686	250	117625.76	892.5
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
250	20.83	90	9802.15	103.41	74.37	
			β_0	β_{tmonth}	β_{thour}	β_{tcycle}
			146.8790	11.839		

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 5	REP-H-C	ZP650-SC-M-B-3	Oxigen Bottle	1	Linear Regression	$1,923.08
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	17	0	17	299.12	101.74
Feb	2	8	1	7	52.66	90.71
Mar	3	0	2	-2	3.17	#DIV/0!
Apr	4	3	3	0	0.03	6.03
May	5	1	4	-3	8.16	285.70
Jun	6	4	5	-1	0.80	22.38
Jul	7	6	6	0	0.00	1.12
Aug	8	2	7	-5	24.71	248.55
Sep	9	0	8	-8	64.14	#DIV/0!
Oct	10	9	9	0	0.00	0.52
Nov	11	8	10	-2	4.35	26.06
Dec	12	7	11	-4	17.00	58.90
Sums		65	65	0	474.16	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
0	0.00	4	39.51	6.57	#DIV/0!	
			β_0	β_{tmonth}	β_{thour}	β_{tcycle}
			-1.333	1.038		

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 6	REP-H-S	2-1517	Brake Assy	3	Linear Regression	$3,762.29
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	0	3	-3	6.46	#DIV/0!
Feb	2	1	3	-2	2.47	157.28
Mar	3	3	3	0	0.18	14.23
Apr	4	2	3	-1	0.36	30.09
May	5	4	2	2	2.67	40.85
Jun	6	3	2	1	0.52	24.07
Jul	7	3	2	1	0.30	18.25
Aug	8	1	2	-1	2.17	147.42
Sep	9	6	2	4	13.00	60.09
Oct	10	3	2	1	0.32	18.95
Nov	11	3	2	1	0.30	18.22
Dec	12	5	2	3	6.27	50.07
Sums		34	30	4	35.03	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
4	0.36	1	2.92	1.78	#DIV/0!	
			β_0	β_{tmonth}	β_{thour}	β_{tcycle}
			2.247	0.07815	0.008334	-0.00475

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 7	REP-L-C	622-2362-001	Receiver ADF	1	Linear Regression	$181.29
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	0	1	-1	1.60	#DIV/0!
Feb	2	4	1	3	7.49	68.44
Mar	3	7	1	6	33.46	82.64
Apr	4	1	1	0	0.02	12.48
May	5	0	1	-1	1.36	#DIV/0!
Jun	6	0	1	-1	1.51	#DIV/0!
Jul	7	0	1	-1	1.15	#DIV/0!
Aug	8	0	1	-1	1.42	#DIV/0!
Sep	9	1	1	0	0.03	18.67
Oct	10	1	1	0	0.00	2.57
Nov	11	1	1	0	0.02	12.92
Dec	12	0	1	-1	1.35	#DIV/0!
Sums		15	14	1	49.42	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	
1	0.08	1	4.12	2.12	#DIV/0!	
			β_0	β_{tcycle}	β_{thour}	β_{tmonth}
			2.669	-0.0007284		

Table No.	Category	Part Number	Name	Parameter	Model	Unit Cost
Qty 8	REP-L-S	DH1030-24-600	Inverter	1	Linear Regression	$1,658.78
Month to be Forecasted	No. Period n	Actual Value Xi	Forecast Value Fi	Error Ei= Xi - Fi	(Error)2 E2	APE (100)*(|Ei| / Xi)
Jan	1	0	0	0	0.01	
Feb	2	0	0	0	0.05	#DIV/0!
Mar	3	1	0	1	0.43	65.50
Apr	4	0	0	0	0.21	#DIV/0!
May	5	1	1	0	0.18	42.50
Jun	6	5	1	4	18.58	86.20
Jul	7	0	1	-1	0.65	#DIV/0!
Aug	8	2	1	1	1.17	54.00
Sep	9	0	1	-1	1.07	#DIV/0!
Oct	10	0	1	-1	1.32	#DIV/0!
Nov	11	0	1	-1	1.60	#DIV/0!
Dec	12	3	1	2	2.62	54.00
Sums		12	9	3	27.90	#DIV/0!
Measures of Accuracy						
CFE	Mean	MAD	MSE	SE	MAPE	COST Error
3	0.25	1	2.32	1.59	#DIV/0!	$5,026.10
			β_0	β_{tcycle}	β_{tmonth}	β_{thour}
			1.318E-16	0.115		

Appendix D: Non-Parametric Tests Observed From Historical Demand Data

	Data	1	2	3	4	5	$[R(X_{ij})]^2$
Quantity No.1	CFE	2	1	3	4	5	55
	ME	2	1	3	4	5	55
61-0478-9	MAD	2	1	3	4	5	55
Consumable	MSE	5	3	1	2	4	55
Low demand	Rj	11	6	10	14	19	220
Specific	Rj^2	121	36	100	196	361	
	ΣRj^2	814					

H_o:All Forecasting Techniques are equal

b=	4	A_2=	220
k=	5	B_2=	203.5
K_1=	4	T_2=	4.27 (T statitstics)
K_2=	12	F (α, K_1, K_2)=	5.412 (critical value)
		Overall p-value=	0.010
		Reject H_o ?	No (T_2>F)

α	$t_{1-\alpha/2,k2}$	$T_{critical}$	MULTIPLE COMPARISON			
0.99	3.05454	10.131	Treat	Rank	I	II
R> $T_{critical}$; next level			F2	6	A	
Note: Adapted from Conover, J. 1980: 300			F3	10	A	B
$\mid R_{fn-1} - R_f \mid > t_{1-\alpha/2}\left[\frac{2b(A_2 - B_2)}{(b-1)(k-1)}\right]^{\frac{1}{2}}$			F1	11	A	B
			F4	14	A	B
			F5	19		B

	Data	1	2	3	4	5	$[R(X_{ij})]^2$
Quantity No.5	CFE	2	1	4	3	5	55
	ME	2	1	4	3	5	55
ZP650-SC-M-B-	MAD	2	1	4	3	5	55
Repairable	MSE	1	3	4	2	5	55
High demand	Rj	7	6	16	11	20	220
Common	Rj^2	49	36	256	121	400	
	ΣRj^2	862					

H_o:All Forecasting Techniques are equal

b=	4	A_2=	220
k=	5	B_2=	215.5
K_1=	4	T_2=	23.67 (T statitstics)
K_2=	12	F (α, K_1, K_2)=	5.412 (critical value)
		Overall p-value=	0.010
		Reject H_o ?	Yes (T_2>F)

α	$t_{1-\alpha/2,k2}$	$T_{critical}$	MULTIPLE COMPARISON				
0.99	3.05454	34.543	Treat	Rank	I	II	III
R> $T_{critical}$; next level			F2	6	A		
Note: Adapted from Conover, J. 1980: 300			F1	7	A		
$\mid R_{fn-1} - R_f \mid > t_{1-\alpha/2}\left[\frac{2b(A_2 - B_2)}{(b-1)(k-1)}\right]^{\frac{1}{2}}$			F4	11	A		
			F3	16	A		
			F5	20	A		

	Data	1	2	3	4	5	$[R(Xij)]^2$
Quantity No.2	CFE	2	1	3	4	5	55
	ME	2	1	3	4	5	55
307	MAD	2	1	3	4	5	55
Consumable	MSE	1	2	3	4	5	55
Low demand	Rj	7	5	12	16	20	220
Common	Rj^2	49	25	144	256	400	
	ΣRj^2	874					

H_o:All Forecasting Techniques are equal

b=	4	A_2=	220
k=	5	B_2=	218.5
K_1=	4	T_2=	77.00 (T statitstics)
K_2=	12	F (α, K_1, K_2)=	5.412 (critical value)
		Overall p-value=	0.010
		Reject H_o ?	Yes (T_2>F)

α	$t_{1-\alpha/2,k2}$	$T_{critical}$	MULTIPLE COMPARISON					
0.99	3.05454	3.055	Treat	Rank	I	II	III	IV
R> $T_{critical}$; next level			F2	5	A			
Note: Adapted from Conover, J. 1980: 300			F1	7	A			
$\lvert R_{fn-1} - R_f \rvert > t_{1-\alpha/2}\left[\frac{2b(A_2-B_2)}{(b-1)(k-1)}\right]^{\frac{1}{2}}$			F3	12		B		
			F4	16			C	
			F5	20				D

	Data	1	2	3	4	5	$[R(Xij)]^2$
Quantity No.6	CFE	2	1	3	5	4	55
	ME	2	1	3	5	4	55
2-1517	MAD	2	1	3	5	4	55
Repairable	MSE	2	5	1	3	4	55
High demand	Rj	8	8	10	18	16	220
Specific	Rj^2	64	64	100	324	256	
	ΣRj^2	808					

H_o:All Forecasting Techniques are equal

b=	4	A_2=	220
k=	5	B_2=	202
K_1=	4	T_2=	3.67 (T statitstics)
K_2=	12	F (α, K_1, K_2)=	5.412 (critical value)
		Overall p-value=	0.010
		Reject H_o ?	No (T_2>F)

α	$t_{1-\alpha/2,k2}$	$T_{critical}$	MULTIPLE COMPARISON			
0.99	3.05454	35.123	Treat	Rank	I	II
R> $T_{critical}$; next level			F2	8	A	
Note: Adapted from Conover, J. 1980: 300			F1	8	A	
$\lvert R_{fn-1} - R_f \rvert > t_{1-\alpha/2}\left[\frac{2b(A_2-B_2)}{(b-1)(k-1)}\right]^{\frac{1}{2}}$			F3	10	A	
			F5	16	A	
			F4	18	A	

	Data	1	2	3	4	5	$[R(X_{ij})]^2$
Quantity No.3	CFE	4	1	2	3	5	55
	ME	4	1	2	3	5	55
F1815/WW/RS	MAD	4	2	1	3	5	55
Consumable	MSE	2	5	1	3	4	55
High demand	Rj	14	9	6	12	19	220
Specific	Rj^2	196	81	36	144	361	
	ΣRj^2	818					

H_o:All Forecasting Techniques are equal

b=	4	A_2=	220
k=	5	B_2=	204.5
K_1=	4	T_2=	4.74 (T statitstics)
K_2=	12	F (α, K_1, K_2)	5.412 (critical value)
		Overall p-value=	0.010
		Reject H_o ?	No (T_2>F)

α	$t_{1-\alpha/2,k2}$	$T_{critical}$	MULTIPLE COMPARISON				
0.99	3.05454	9.819	Treat	Rank	I	II	III
R> $T_{critical}$; next level			F3	6	A		
Note: Adapted from Conover, J. 1980: 300			F2	9	A	B	
$\lvert R_{fn-1} - R_f \rvert > t_{1-\alpha/2}\left[\frac{2b(A_2 - B_2)}{(b-1)(k-1)}\right]^{\frac{1}{2}}$			F4	12	A	B	C
			F1	14	A	B	C
			F5	19	FALSE	FALSE	C

	Data	1	2	3	4	5	$[R(X_{ij})]^2$
Quantity No.7	CFE	2.5	4	5	2.5	1	54.5
	ME	2.5	4	5	2.5	1	54.5
622-2362-001	MAD	2	4	5	3	1	55
Repairable	MSE	2	5	3	4	1	55
Low demand	Rj	9	17	18	12	4	219
Common	Rj^2	81	289	324	144	16	
	ΣRj^2	854					

H_o:All Forecasting Techniques are equal

b=	4	A_2=	219
k=	5	B_2=	213.5
K_1=	4	T_2=	18.27 (T statitstics)
K_2=	12	F (α, K_1, K_2)=	5.412 (critical value)
		Overall p-value=	0.010
		Reject H_o ?	Yes (T_2>F)

α	$t_{1-\alpha/2,k2}$	$T_{critical}$	MULTIPLE COMPARISON					
0.99	3.05454	34.847	Treat	Rank	I	II	III	IV
R> $T_{critical}$; next level			F5	4	A			
Note: Adapted from Conover, J. 1980: 300			F1	9	A			
$\lvert R_{fn-1} - R_f \rvert > t_{1-\alpha/2}\left[\frac{2b(A_2 - B_2)}{(b-1)(k-1)}\right]^{\frac{1}{2}}$			F4	12	A			
			F2	17	A			
			F3	18	A			

	Data	1	2	3	4	5	$[R(X_{ij})]^2$
Quantity No.4	CFE	1.5	4	1.5	3	5	54.5
	ME	1.5	4	1.5	3	5	54.5
MS24665-134	MAD	2	4	1	3	5	55
Consumable	MSE	1	4	2	3	5	55
High demand	Rj	6	16	6	12	20	219
Common	Rj^2	36	256	36	144	400	
	ΣRj^2	872					

H_o:All Forecasting Techniques are equal

b=	4	A_2=	219
k=	5	B_2=	218
K_1=	4	T_2=	114.00 (T statitstics)
K_2=	12	F (α, K_1, K_2)	5.412 (critical value)
		Overall p-value=	0.010
		Reject H_o ?	Yes (T_2>F)

α	$t_{1-\alpha/2,k2}$	$T_{critical}$	MULTIPLE COMPARISON					
0.99	3.05454	2.494	Treat	Rank	I	II	III	IV
R> $T_{critical}$: next level			F1	6	A			
Note: Adapted from Conover, J. 1980: 300			F3	6	A			
$\lvert R_{fn-1} - R_f \rvert > t_{1-\alpha/2}\left[\frac{2b(A_2-B_2)}{(b-1)(k-1)}\right]^{\frac{1}{2}}$			F4	12		B		
			F2	16			C	
			F5	20				D

	Data	1	2	3	4	5	$[R(X_{ij})]^2$
Quantity No.8	CFE	2.5	2.5	1	4.5	4.5	54
	ME	2.5	2.5	1	4.5	4.5	54
DH1030-24-600	MAD	2.5	2.5	1	5	4	54.5
Repairable	MSE	4	5	1	2	3	55
Low demand	Rj	11.5	12.5	4	16	16	217.5
Specific	Rj^2	132.25	156.25	16	256	256	
	ΣRj^2	816.5					

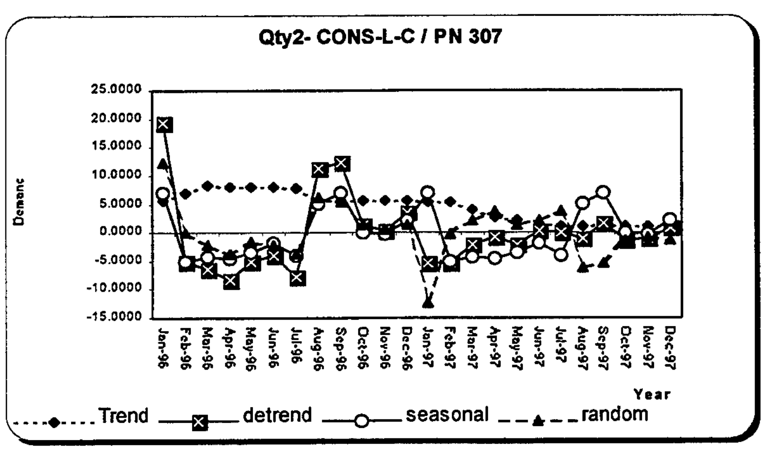
H_o:All Forecasting Techniques are equal

b=	4	A_2=	217.5
k=	5	B_2=	204.125
K_1=	4	T_2=	5.41 (T statitstics)
K_2=	12	F (α, K_1, K_2)=	5.412 (critical value)
		Overall p-value=	0.010
		Reject H_o ?	No (T_2>F)

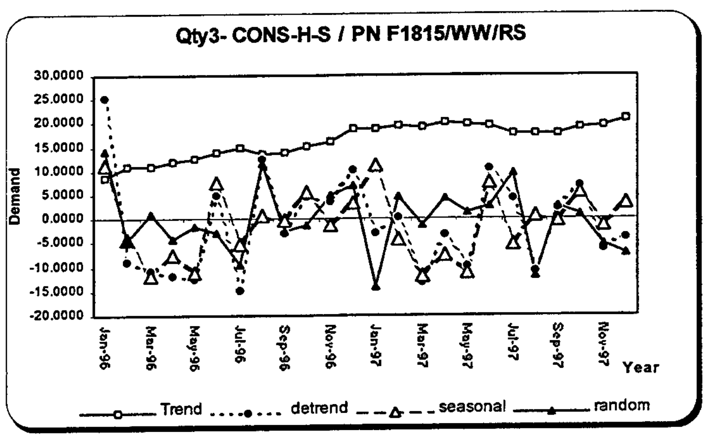
α	$t_{1-\alpha/2,k2}$	$T_{critical}$	MULTIPLE COMPARISON			
0.99	3.05454	35.157	Treat	Rank	I	II
R> $T_{critical}$: next level			F3	4	A	
Note: Adapted from Conover, J. 1980: 300			F1	11.5	A	
$\lvert R_{fn-1} - R_f \rvert > t_{1-\alpha/2}\left[\frac{2b(A_2-B_2)}{(b-1)(k-1)}\right]^{\frac{1}{2}}$			F2	12.5	A	
			F4	16	A	
			F5	16	A	

Appendix E: Decomposition of Historical Demand Data

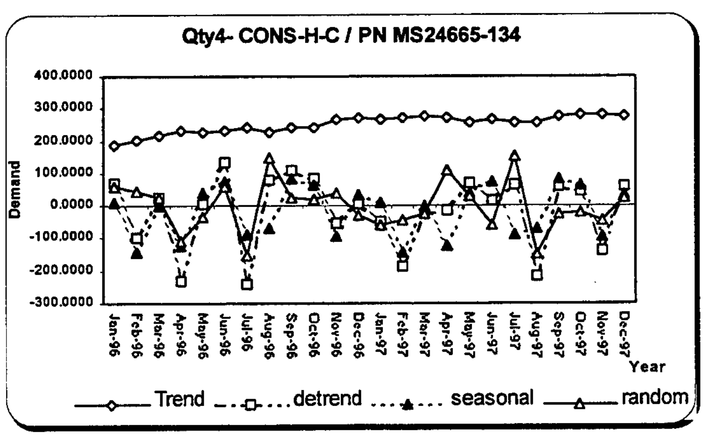
CONS-L-C	307	Trend	Detrend	Seasonal	Irregular
Month	Obs (Yt)	12 MA (Tt)	Yt-Tt	St	Et
Jan-96	25	5.5385	19.4615	7.0641	12.3974
Feb-96	2	7.0667	-5.0667	-5.2000	0.1333
Mar-96	2	8.3529	-6.3529	-4.2598	-2.0931
Apr-96	0	8.2105	-8.2105	-4.4386	-3.7719
May-96	3	8.0000	-5.0000	-3.5417	-1.4583
Jun-96	4	8.0870	-4.0870	-1.9185	-2.1685
Jul-96	0	7.7500	-7.7500	-3.8967	-3.8533
Aug-96	17	5.6667	11.3333	5.0952	6.2381
Sep-96	18	5.6667	12.3333	7.0351	5.2982
Oct-96	7	5.6667	1.3333	0.0784	1.2549
Nov-96	6	5.6667	0.3333	-0.3667	0.7000
Dec-96	9	5.5833	3.4167	2.0929	1.3237
Jan-97	0	5.3333	-5.3333	7.0641	-12.3974
Feb-97	0	5.3333	-5.3333	-5.2000	-0.1333
Mar-97	2	4.1667	-2.1667	-4.2598	2.0931
Apr-97	2	2.6667	-0.6667	-4.4386	3.7719
May-97	0	2.0833	-2.0833	-3.5417	1.4583
Jun-97	2	1.7500	0.2500	-1.9185	2.1685
Jul-97	1	1.0435	-0.0435	-3.8967	3.8533
Aug-97	0	1.1429	-1.1429	5.0952	-6.2381
Sep-97	3	1.2632	1.7368	7.0351	-5.2982
Oct-97	0	1.1765	-1.1765	0.0784	-1.2549
Nov-97	0	1.0667	-1.0667	-0.3667	-0.7000
Dec-97	2	1.2308	0.7692	2.0929	-1.3237
Grand Tot	105				



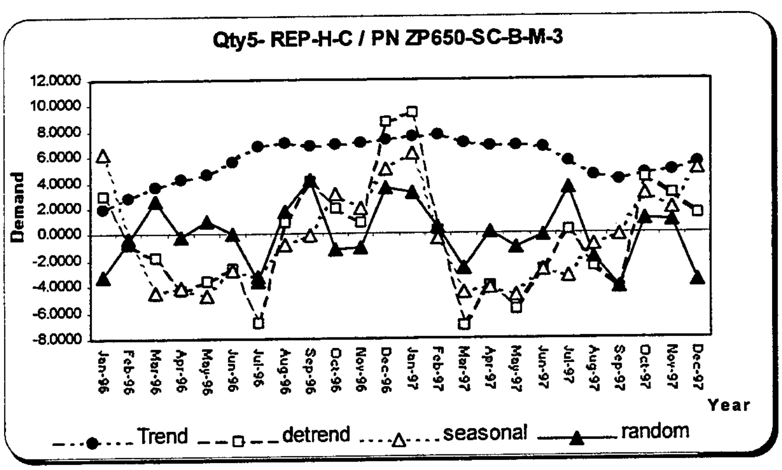
CONS-H-S	F1815/WW/RS	Trend	Detrend	Seasonal	Irregular
Month	Obs (Yt)	12 MA (Tt)	Yt-Tt	St	Et
Jan-96	34	8.4615	25.5385	11.3109	14.2276
Feb-96	2	10.8000	-8.8000	-4.1500	-4.6500
Mar-96	0	10.8235	-10.8235	-11.9118	1.0882
Apr-96	0	11.7895	-11.7895	-7.5197	-4.2697
May-96	0	12.5714	-12.5714	-11.1190	-1.4524
Jun-96	19	14.0000	5.0000	7.7917	-2.7917
Jul-96	0	14.7500	-14.7500	-5.2446	-9.5054
Aug-96	26	13.5833	12.4167	0.7560	11.6607
Sep-96	11	13.9167	-2.9167	-0.3004	-2.6162
Oct-96	20	15.3333	4.6667	5.8039	-1.1373
Nov-96	20	16.1667	3.8333	-1.2500	5.0833
Dec-96	29	18.6667	10.3333	3.2821	7.0513
Jan-97	16	18.9167	-2.9167	11.3109	-14.2276
Feb-97	20	19.5000	0.5000	-4.1500	4.6500
Mar-97	6	19.0000	-13.0000	-11.9118	-1.0882
Apr-97	17	20.2500	-3.2500	-7.5197	4.2697
May-97	10	19.6667	-9.6667	-11.1190	1.4524
Jun-97	30	19.4167	10.5833	7.7917	2.7917
Jul-97	22	17.7391	4.2609	-5.2446	9.5054
Aug-97	7	17.9048	-10.9048	0.7560	-11.6607
Sep-97	20	17.6842	2.3158	-0.3004	2.6162
Oct-97	26	19.0588	6.9412	5.8039	1.1373
Nov-97	13	19.3333	-6.3333	-1.2500	-5.0833
Dec-97	17	20.7692	-3.7692	3.2821	-7.0513
Grand Total	365				



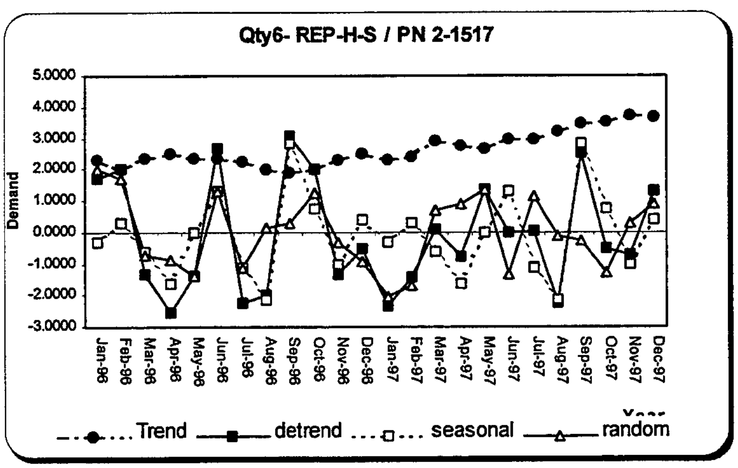
CONS-H-C	MS24665-134	Trend	Detrend	Seasonal	Irregular
Month	Obs (Yt)	12 MA (Tt)	Yt-Tt	St	Et
Jan-96	257	186.3077	70.6923	12.01282051	58.6795
Feb-96	104	202.2667	-98.2667	-142.716667	44.4500
Mar-96	245	219.7647	25.2353	0.742647059	24.4926
Apr-96	0	230.8421	-230.8421	-123.254386	-107.5877
May-96	236	229.3333	6.6667	38.45833333	-31.7917
Jun-96	369	233.5652	135.4348	75.80072464	59.6341
Jul-96	0	242.3333	-242.3333	-87.8188406	-154.5145
Aug-96	306	228.0000	78.0000	-69.2380952	147.2381
Sep-96	351	240.2500	110.7500	85.50657895	25.2434
Oct-96	325	241.2500	83.7500	64.99264706	18.7574
Nov-96	215	268.5833	-53.5833	-95.1916667	41.6083
Dec-96	278	272.5833	5.4167	32.78525641	-27.3686
Jan-97	222	268.6667	-46.6667	12.01282051	-58.6795
Feb-97	85	272.1667	-187.1667	-142.716667	-44.4500
Mar-97	251	274.7500	-23.7500	0.742647059	-24.4926
Apr-97	257	272.6667	-15.6667	-123.254386	107.5877
May-97	328	257.7500	70.2500	38.45833333	31.7917
Jun-97	284	267.8333	16.1667	75.80072464	-59.6341
Jul-97	322	255.3043	66.6957	-87.8188406	154.5145
Aug-97	42	258.4762	-216.4762	-69.2380952	-147.2381
Sep-97	337	276.7368	60.2632	85.50657895	-25.2434
Oct-97	326	279.7647	46.2353	64.99264706	-18.7574
Nov-97	146	282.8000	-136.8000	-95.1916667	-41.6083
Dec-97	336	275.8462	60.1538	32.78525641	27.3686
Grand Total	5622				



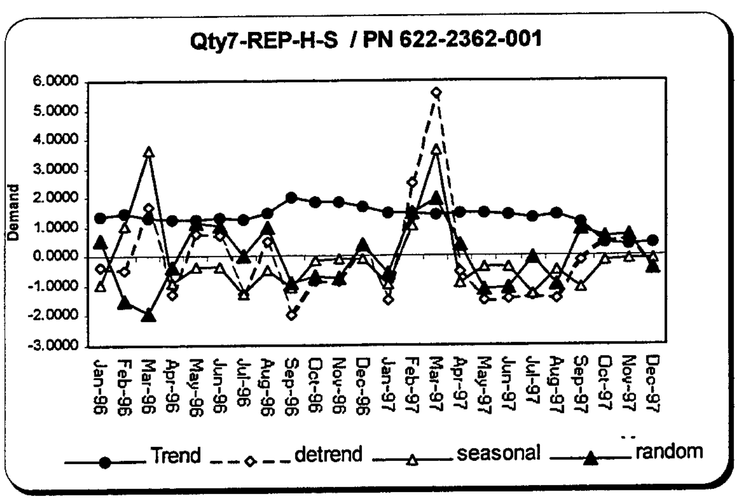
REP-H-C	ZP650-SC-M-B-3	Trend	Detrend	Seasonal	Irregular
Month	Obs (Yt)	12 MA (Tt)	Yt-Tt	St	Et
Jan-96	5	2.0000	3.0000	6.2083	-3.2083
Feb-96	2	2.8000	-0.8000	-0.2750	-0.5250
Mar-96	2	3.7647	-1.7647	-4.4240	2.6593
Apr-96	0	4.3158	-4.3158	-4.1162	-0.1996
May-96	1	4.6667	-3.6667	-4.7500	1.0833
Jun-96	3	5.6522	-2.6522	-2.7011	0.0489
Jul-96	0	6.8333	-6.8333	-3.2428	-3.5906
Aug-96	8	7.0833	0.9167	-0.8274	1.7440
Sep-96	11	6.9167	4.0833	-0.0636	4.1469
Oct-96	9	7.0000	2.0000	3.1471	-1.1471
Nov-96	8	7.0833	0.9167	1.9917	-1.0750
Dec-96	16	7.3333	8.6667	5.0641	3.6026
Jan-97	17	7.5833	9.4167	6.2083	3.2083
Feb-97	8	7.7500	0.2500	-0.2750	0.5250
Mar-97	0	7.0833	-7.0833	-4.4240	-2.6593
Apr-97	3	6.9167	-3.9167	-4.1162	0.1996
May-97	1	6.8333	-5.8333	-4.7500	-1.0833
Jun-97	4	6.7500	-2.7500	-2.7011	-0.0489
Jul-97	6	5.6522	0.3478	-3.2428	3.5906
Aug-97	2	4.5714	-2.5714	-0.8274	-1.7440
Sep-97	0	4.2105	-4.2105	-0.0636	-4.1469
Oct-97	9	4.7059	4.2941	3.1471	1.1471
Nov-97	8	4.9333	3.0667	1.9917	1.0750
Dec-97	7	5.5385	1.4615	5.0641	-3.6026
Grand Total	94				



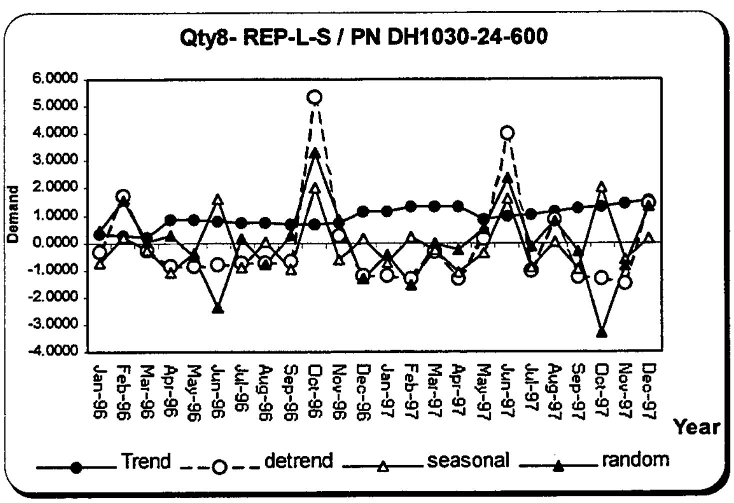
REP-H-S	2-1517	Trend	Detrend	Seasonal	Irregular
Month	Obs (Yt)	12 MA (Tt)	Yt-Tt	St	Et
Jan-96	4	2.3077	1.6923	-0.32051	2.0128
Feb-96	4	2.0000	2.0000	0.29167	1.7083
Mar-96	1	2.3529	-1.3529	-0.63480	-0.7181
Apr-96	0	2.5263	-2.5263	-1.63816	-0.8882
May-96	1	2.3810	-1.3810	-0.02381	-1.3571
Jun-96	5	2.3478	2.6522	1.32609	1.3261
Jul-96	0	2.2500	-2.2500	-1.10326	-1.1467
Aug-96	0	2.0000	-2.0000	-2.11905	0.1190
Sep-96	5	1.9167	3.0833	2.80482	0.2785
Oct-96	4	2.0000	2.0000	0.73529	1.2647
Nov-96	1	2.3333	-1.3333	-1.03333	-0.3000
Dec-96	2	2.5000	-0.5000	0.40385	-0.9038
Jan-97	0	2.3333	-2.3333	-0.32051	-2.0128
Feb-97	1	2.4167	-1.4167	0.29167	-1.7083
Mar-97	3	2.9167	0.0833	-0.63480	0.7181
Apr-97	2	2.7500	-0.7500	-1.63816	0.8882
May-97	4	2.6667	1.3333	-0.02381	1.3571
Jun-97	3	3.0000	0.0000	1.32609	-1.3261
Jul-97	3	2.9565	0.0435	-1.10326	1.1467
Aug-97	1	3.2381	-2.2381	-2.11905	-0.1190
Sep-97	6	3.4737	2.5263	2.80482	-0.2785
Oct-97	3	3.5294	-0.5294	0.73529	-1.2647
Nov-97	3	3.7333	-0.7333	-1.03333	0.3000
Dec-97	5	3.6923	1.3077	0.40385	0.9038
Grand Total	61				



REP-L-C	622-2362-001	Trend	Detrend	Seasonal	Irregular
Month	Obs (Yt)	12 MA (Tt)	Yt-Tt	St	Et
Jan-96	1	1.3846	-0.3846	-0.9423	0.5577
Feb-96	1	1.4667	-0.4667	1.0167	-1.4833
Mar-96	3	1.2941	1.7059	3.6446	-1.9387
Apr-96	0	1.2632	-1.2632	-0.8816	-0.3816
May-96	2	1.2381	0.7619	-0.3690	1.1310
Jun-96	2	1.3043	0.6957	-0.3605	1.0562
Jul-96	0	1.2500	-1.2500	-1.2772	0.0272
Aug-96	2	1.5000	0.5000	-0.4643	0.9643
Sep-96	0	2.0000	-2.0000	-1.0789	-0.9211
Oct-96	1	1.8333	-0.8333	-0.1520	-0.6814
Nov-96	1	1.8333	-0.8333	-0.1167	-0.7167
Dec-96	2	1.6667	0.3333	-0.0641	0.3974
Jan-97	0	1.5000	-1.5000	-0.9423	-0.5577
Feb-97	4	1.5000	2.5000	1.0167	1.4833
Mar-97	7	1.4167	5.5833	3.6446	1.9387
Apr-97	1	1.5000	-0.5000	-0.8816	0.3816
May-97	0	1.5000	-1.5000	-0.3690	-1.1310
Jun-97	0	1.4167	-1.4167	-0.3605	-1.0562
Jul-97	0	1.3043	-1.3043	-1.2772	-0.0272
Aug-97	0	1.4286	-1.4286	-0.4643	-0.9643
Sep-97	1	1.1579	-0.1579	-1.0789	0.9211
Oct-97	1	0.4706	0.5294	-0.1520	0.6814
Nov-97	1	0.4000	0.6000	-0.1167	0.7167
Dec-97	0	0.4615	-0.4615	-0.0641	-0.3974
Grand Total	30				



REP-L-S	DH1030-24-600CS	Trend	Detrend	Seasonal	Irregular
Month	Obs (Yt)	12 MA (Tt)	Yt-Tt	St	Et
Jan-96	0	0.3077	-0.3077	-0.7372	0.4295
Feb-96	2	0.2667	1.7333	0.2000	1.5333
Mar-96	0	0.2353	-0.2353	-0.2843	0.0490
Apr-96	0	0.8421	-0.8421	-1.0877	0.2456
May-96	0	0.8571	-0.8571	-0.3452	-0.5119
Jun-96	0	0.7826	-0.7826	1.6087	-2.3913
Jul-96	0	0.7500	-0.7500	-0.8967	0.1467
Aug-96	0	0.7500	-0.7500	0.0536	-0.8036
Sep-96	0	0.6667	-0.6667	-0.9649	0.2982
Oct-96	6	0.6667	5.3333	2.0196	3.3137
Nov-96	1	0.7500	0.2500	-0.6083	0.8583
Dec-96	0	1.1667	-1.1667	0.1474	-1.3141
Jan-97	0	1.1667	-1.1667	-0.7372	-0.4295
Feb-97	0	1.3333	-1.3333	0.2000	-1.5333
Mar-97	1	1.3333	-0.3333	-0.2843	-0.0490
Apr-97	0	1.3333	-1.3333	-1.0877	-0.2456
May-97	1	0.8333	0.1667	-0.3452	0.5119
Jun-97	5	1.0000	4.0000	1.6087	2.3913
Jul-97	0	1.0435	-1.0435	-0.8967	-0.1467
Aug-97	2	1.1429	0.8571	0.0536	0.8036
Sep-97	0	1.2632	-1.2632	-0.9649	-0.2982
Oct-97	0	1.2941	-1.2941	2.0196	-3.3137
Nov-97	0	1.4667	-1.4667	-0.6083	-0.8583
Dec-97	3	1.5385	1.4615	0.1474	1.3141
Grand Total	21				



Appendix F: Kolmogorov Test for The Uniform Distribution

CONS-L-C	307	KOLMOGOROV-SMIRNOV TEST- UNIFORM				
I	Transformed	Ranked	Normalized	I/N	D+	D-
1	172.3974	147.603	0.038	0.04	0.0032	0.038
2	160.1333	153.762	0.078	0.08	0.0049	0.037
3	157.9069	154.702	0.119	0.13	0.0062	0.035
4	156.2281	156.147	0.159	0.17	0.0072	0.034
2	158.5417	156.228	0.200	0.08	0.0000	0.033
6	157.8315	157.832	0.241	0.25	0.0088	0.158
7	156.1467	157.907	0.282	0.29	0.0093	0.032
8	166.2381	158.542	0.324	0.33	0.0097	0.032
9	165.2982	158.676	0.365	0.38	0.0101	0.032
10	161.2549	158.745	0.406	0.42	0.0104	0.031
11	160.7000	159.300	0.448	0.46	0.0106	0.031
12	161.3237	159.867	0.489	0.50	0.0106	0.031
13	147.6026	160.133	0.531	0.54	0.0106	0.031
14	159.8667	160.700	0.573	0.58	0.0104	0.031
15	162.0931	161.255	0.615	0.63	0.0101	0.032
16	163.7719	161.324	0.657	0.67	0.0097	0.032
17	161.4583	161.458	0.699	0.71	0.0093	0.032
18	162.1685	162.093	0.741	0.75	0.0088	0.033
19	163.8533	162.168	0.783	0.79	0.0082	0.033
20	153.7619	163.772	0.826	0.83	0.0072	0.034
21	154.7018	163.853	0.869	0.88	0.0062	0.035
22	158.7451	165.298	0.912	0.92	0.0049	0.037
23	159.3000	166.238	0.955	0.96	0.0032	0.038
24	158.6763	172.397	1.000	1	0.0000	0.042
	Sum	3840		MAX	0.010596581	0.157883478

H_0: Irregular component is uniform distributed

D= 0.157883478

α= 0.05

N= 24

D(a,N)= 0.277608838 (critical value)

Reject H_0? **NO** (D< D(a,N))

CONS-H-S	F1815/WW/RS	KOLMOGOROV-SMIRNOV TEST- UNIFORM				
I	Transformed	Ranked	Normalized	I/N	D^+	D-
1	174.2276	145.772	0.038	0.04	0.0037	0.038
2	155.3500	148.339	0.077	0.08	0.0067	0.035
3	161.0882	150.495	0.116	0.13	0.0092	0.032
4	155.7303	152.949	0.156	0.17	0.0111	0.031
2	158.5476	154.917	0.196	0.08	0.0000	0.029
6	157.2083	155.350	0.236	0.25	0.0136	0.153
7	150.4946	155.730	0.277	0.29	0.0147	0.027
8	171.6607	157.208	0.318	0.33	0.0154	0.026
9	157.3838	157.384	0.359	0.38	0.0161	0.026
10	158.8627	158.548	0.400	0.42	0.0165	0.025
11	165.0833	158.863	0.442	0.46	0.0168	0.025
12	167.0513	158.912	0.483	0.50	0.0171	0.025
13	145.7724	161.088	0.525	0.54	0.0168	0.025
14	164.6500	161.137	0.567	0.58	0.0165	0.025
15	158.9118	161.452	0.609	0.63	0.0161	0.026
16	164.2697	162.616	0.651	0.67	0.0154	0.026
17	161.4524	162.792	0.694	0.71	0.0147	0.027
18	162.7917	164.270	0.736	0.75	0.0136	0.028
19	169.5054	164.650	0.779	0.79	0.0124	0.029
20	148.3393	165.083	0.822	0.83	0.0111	0.031
21	162.6162	167.051	0.866	0.88	0.0092	0.032
22	161.1373	169.505	0.910	0.92	0.0067	0.035
23	154.9167	171.661	0.955	0.96	0.0037	0.038
24	152.9487	174.228	1.000	1	0.0000	0.042
	Sum	3840		MAX	0.017066102	0.15307856

H_0: **Irregular component is uniform distributed**

D= 0.15307856

a= 0.05

N= 24

D(a,N) = 0.277608838 (critical value)

Reject H_0? NO (D< D(a,N))

CONS-H-C	MS24665-134	KOLMOGOROV-SMIRNOV TEST- UNIFORM				
I	Transformed	Ranked	Normalized	I/N	D^+	D-
1	218.6795	5.486	0.001	0.04	0.0402	0.001
2	204.4500	12.762	0.005	0.08	0.0786	0.000
3	184.4926	52.412	0.018	0.13	0.1066	0.000
4	52.4123	100.366	0.045	0.17	0.1221	0.000
2	128.2083	101.321	0.071	0.08	0.0124	0.000
6	219.6341	115.550	0.101	0.25	0.1490	0.018
7	5.4855	118.392	0.132	0.29	0.1598	0.000
8	307.2381	128.208	0.165	0.33	0.1681	0.000
9	185.2434	132.631	0.200	0.38	0.1752	0.000
10	178.7574	134.757	0.235	0.42	0.1818	0.000
11	201.6083	135.507	0.270	0.46	0.1882	0.000
12	132.6314	141.243	0.307	0.50	0.1931	0.000
13	101.3205	178.757	0.353	0.54	0.1882	0.000
14	115.5500	184.493	0.402	0.58	0.1818	0.000
15	135.5074	185.243	0.450	0.63	0.1752	0.000
16	267.5877	187.369	0.499	0.67	0.1681	0.000
17	191.7917	191.792	0.549	0.71	0.1598	0.000
18	100.3659	201.608	0.601	0.75	0.1490	0.000
19	314.5145	204.450	0.654	0.79	0.1374	0.000
20	12.7619	218.679	0.711	0.83	0.1221	0.000
21	134.7566	219.634	0.768	0.88	0.1066	0.000
22	141.2426	267.588	0.838	0.92	0.0786	0.000
23	118.3917	307.238	0.918	0.96	0.0402	0.001
24	187.3686	314.514	1.000	1	0.0000	0.042
	Sum	3840		MAX	0.19306	0.04167

H_0 : Irregular component is uniform distributed

D = 0.193064027

a= 0.05

N= 24

D(a,N) = 0.277608838 (critical value)

Reject H_0? **NO** (D< D(a,N))

REP-H-C	ZP650-SC-M-B-3	KOLMOGOROV-SMIRNOV TEST- UNIFORM				
I	Transformed	Ranked	Normalized	I/N	D^+	D-
1	156.7917	155.853	0.041	0.04	0.0011	0.041
2	159.4750	156.397	0.081	0.08	0.0020	0.040
3	162.6593	156.409	0.122	0.13	0.0030	0.039
4	159.8004	156.792	0.163	0.17	0.0038	0.038
2	161.0833	157.341	0.204	0.08	0.0000	0.037
6	160.0489	158.256	0.245	0.25	0.0049	0.162
7	156.4094	158.853	0.286	0.29	0.0052	0.036
8	161.7440	158.917	0.328	0.33	0.0055	0.036
9	164.1469	158.925	0.369	0.38	0.0058	0.036
10	158.8529	159.475	0.411	0.42	0.0059	0.036
11	158.9250	159.800	0.452	0.46	0.0060	0.036
12	163.6026	159.951	0.494	0.50	0.0060	0.036
13	163.2083	160.049	0.536	0.54	0.0060	0.036
14	160.5250	160.200	0.577	0.58	0.0059	0.036
15	157.3407	160.525	0.619	0.63	0.0058	0.036
16	160.1996	161.075	0.661	0.67	0.0055	0.036
17	158.9167	161.083	0.703	0.71	0.0052	0.036
18	159.9511	161.147	0.745	0.75	0.0049	0.037
19	163.5906	161.744	0.787	0.79	0.0045	0.037
20	158.2560	162.659	0.830	0.83	0.0038	0.038
21	155.8531	163.208	0.872	0.88	0.0030	0.039
22	161.1471	163.591	0.915	0.92	0.0020	0.040
23	161.0750	163.603	0.957	0.96	0.0011	0.041
24	156.3974	164.147	1.000	1	0.0000	0.042
	Sum	3840		MAX	0.005997561	0.16173131

H_0 :	**Irregular component is uniform distributed**
D =	0.16173131
a=	0.05
N=	24
D(a,N) =	0.277608838 (critical value)
Reject H_0?	NO (D< D(a,N))

REP-H-S	2-1517	KOLMOGOROV-SMIRNOV TEST- UNIFORM				
I	Transformed	Ranked	Normalized	I/N	D^+	D-
1	162.0128	157.987	0.041	0.04	0.0005	0.041
2	161.7083	158.292	0.082	0.08	0.0010	0.041
3	159.2819	158.643	0.124	0.13	0.0013	0.040
4	159.1118	158.674	0.165	0.17	0.0017	0.040
2	158.6429	158.735	0.206	0.08	0.0000	0.040
6	161.3261	158.853	0.248	0.25	0.0023	0.164
7	158.8533	159.096	0.289	0.29	0.0025	0.039
8	160.1190	159.112	0.331	0.33	0.0028	0.039
9	160.2785	159.282	0.372	0.38	0.0029	0.039
10	161.2647	159.700	0.414	0.42	0.0030	0.039
11	159.7000	159.721	0.455	0.46	0.0031	0.039
12	159.0962	159.881	0.497	0.50	0.0031	0.039
13	157.9872	160.119	0.539	0.54	0.0031	0.039
14	158.2917	160.279	0.580	0.58	0.0030	0.039
15	160.7181	160.300	0.622	0.63	0.0029	0.039
16	160.8882	160.718	0.664	0.67	0.0028	0.039
17	161.3571	160.888	0.706	0.71	0.0025	0.039
18	158.6739	160.904	0.748	0.75	0.0023	0.039
19	161.1467	161.147	0.790	0.79	0.0020	0.040
20	159.8810	161.265	0.832	0.83	0.0017	0.040
21	159.7215	161.326	0.874	0.88	0.0013	0.040
22	158.7353	161.357	0.916	0.92	0.0010	0.041
23	160.3000	161.708	0.958	0.96	0.0005	0.041
24	160.9038	162.013	1.000	1	0.0000	0.042
	Sum	3840		MAX	0.003131	0.164371

H_0 :	**Irregular component is uniform distributed**
D =	0.164370878
a=	0.05
N=	24
D(a,N) =	0.277609 (critical value)
Reject H_0?	**NO** (D< D(a,N))

REP-L-C	622-2362-001	KOLMOGOROV-SMIRNOV TEST- UNIFORM				
I	Transformed	Ranked	Normalized	I/N	D+	D-
1	160.5577	158.061	0.041	0.04	0.0005	0.041
2	158.5167	158.517	0.082	0.08	0.0009	0.041
3	158.0613	158.869	0.124	0.13	0.0012	0.040
4	159.6184	158.944	0.165	0.17	0.0015	0.040
2	161.1310	159.036	0.207	0.08	0.0000	0.040
6	161.0562	159.079	0.248	0.25	0.0020	0.165
7	160.0272	159.283	0.290	0.29	0.0021	0.040
8	160.9643	159.319	0.331	0.33	0.0023	0.039
9	159.0789	159.442	0.373	0.38	0.0025	0.039
10	159.3186	159.603	0.414	0.42	0.0026	0.039
11	159.2833	159.618	0.456	0.46	0.0027	0.039
12	160.3974	159.973	0.497	0.50	0.0027	0.039
13	159.4423	160.027	0.539	0.54	0.0027	0.039
14	161.4833	160.382	0.581	0.58	0.0026	0.039
15	161.9387	160.397	0.623	0.63	0.0025	0.039
16	160.3816	160.558	0.664	0.67	0.0023	0.039
17	158.8690	160.681	0.706	0.71	0.0021	0.040
18	158.9438	160.717	0.748	0.75	0.0020	0.040
19	159.9728	160.921	0.790	0.79	0.0017	0.040
20	159.0357	160.964	0.832	0.83	0.0015	0.040
21	160.9211	161.056	0.874	0.88	0.0012	0.040
22	160.6814	161.131	0.916	0.92	0.0009	0.041
23	160.7167	161.483	0.958	0.96	0.0005	0.041
24	159.6026	161.939	1.000	1	0.0000	0.042
	Sum	**3840**		**MAX**	**0.00267**	**0.16471**

H_0 : **Irregular component is uniform distributed**

D = 0.16471

a= 0.05

N= 24

D(a,N) = 0.27761 (critical value)

Reject H_0? NO (D< D(a,N))

REP-L-S	DH1030-24-600CS	KOLMOGOROV-SMIRNOV TEST- UNIFORM				
I	Transformed	Ranked	Normalized	I/N	D+	D-
1	160.4295	156.686	0.041	0.04	0.0009	0.041
2	161.5333	157.609	0.082	0.08	0.0015	0.040
3	160.0490	158.467	0.123	0.13	0.0019	0.040
4	160.2456	158.686	0.164	0.17	0.0022	0.039
2	159.4881	159.142	0.206	0.08	0.0000	0.039
6	157.6087	159.196	0.247	0.25	0.0027	0.164
7	160.1467	159.488	0.289	0.29	0.0028	0.039
8	159.1964	159.571	0.330	0.33	0.0029	0.039
9	160.2982	159.702	0.372	0.38	0.0030	0.039
10	163.3137	159.754	0.414	0.42	0.0030	0.039
11	160.8583	159.853	0.455	0.46	0.0031	0.039
12	158.6859	159.951	0.497	0.50	0.0031	0.039
13	159.5705	160.049	0.539	0.54	0.0031	0.039
14	158.4667	160.147	0.580	0.58	0.0030	0.039
15	159.9510	160.246	0.622	0.63	0.0030	0.039
16	159.7544	160.298	0.664	0.67	0.0029	0.039
17	160.5119	160.429	0.706	0.71	0.0028	0.039
18	162.3913	160.512	0.747	0.75	0.0027	0.039
19	159.8533	160.804	0.789	0.79	0.0025	0.039
20	160.8036	160.858	0.831	0.83	0.0022	0.039
21	159.7018	161.314	0.873	0.88	0.0019	0.040
22	156.6863	161.533	0.915	0.92	0.0015	0.040
23	159.1417	162.391	0.957	0.96	0.0009	0.041
24	161.3141	163.314	1.000	1	0.0000	0.042
	Sum	**3840**		**MAX**	**0.00310**	**0.16401**

H_0 : **Irregular component is uniform distributed**

D = 0.16401

a= 0.05

N= 24

D(a,N) = 0.27761 (critical value)

Reject H_0? **NO** (D< D(a,N))

Appendix G: Transformation of Simulated Demand Data

Summary Statistics		Model	DV: TREND	Coefficients
Mean	0.0000	Bo	(Constant)	8.921
Standard Deviation	8.3686	B1	PERIOD	-0.34868
Minimum	-12.3974	Excel Formula=Rnguniform(min,max)		
Maximum	12.3974			
Count	24			

CONS-L-C	307	CONVERSION OF SIMULATED IRREGULAR COMPONENT DATA TO ACTUAL SIMULATED DATA					
Month	**Period**	**E't**	**St**	**Bo**	**B1**	**Y't**	**Y't(Trunc,0)**
Jan-96	1	12.9878	7.0641	8.921	-0.3487	29	29
Feb-96	2	14.9878	-5.2000	8.921	-0.6974	18	18
Mar-96	3	-9.0122	-4.2598	8.921	-1.0460	-5	0
Apr-96	4	2.9878	-4.4386	8.921	-1.3947	6	6
May-96	5	-1.0122	-3.5417	8.921	-1.7434	3	3
Jun-96	6	-1.0122	-1.9185	8.921	-2.0921	4	4
Jul-96	7	4.9878	-3.8967	8.921	-2.4407	8	8
Aug-96	8	8.9878	5.0952	8.921	-2.7894	20	20
Sep-96	9	14.9878	7.0351	8.921	-3.1381	28	28
Oct-96	10	-0.0122	0.0784	8.921	-3.4868	6	6
Nov-96	11	6.9878	-0.3667	8.921	-3.8354	12	12
Dec-96	12	5.9878	2.0929	8.921	-4.1841	13	13
Jan-97	13	-2.0122	7.0641	8.921	-4.5328	9	9
Feb-97	14	4.9878	-5.2000	8.921	-4.8815	4	4
Mar-97	15	-1.0122	-4.2598	8.921	-5.2301	-2	0
Apr-97	16	8.9878	-4.4386	8.921	-5.5788	8	8
May-97	17	5.9878	-3.5417	8.921	-5.9275	5	5
Jun-97	18	-6.0122	-1.9185	8.921	-6.2762	-5	0
Jul-97	19	8.9878	-3.8967	8.921	-6.6249	7	7
Aug-97	20	9.9878	5.0952	8.921	-6.9735	17	17
Sep-97	21	1.9878	7.0351	8.921	-7.3222	11	11
Oct-97	22	-3.0122	0.0784	8.921	-7.6709	-2	0
Nov-97	23	-4.0122	-0.3667	8.921	-8.0196	-3	0
Dec-97	24	12.9878	2.0929	8.921	-8.3682	16	16

Summary Statistics		Model	DV: TREND	Coefficients
Mean	0.0000	Bo	(Constant)	10.6751
Standard Devi	10.5693	B1	PERIOD	0.4463
Minimum	-14.2276	Excel Formula=Rnguniform(min,max)		
Maximum	14.2276			
Count	24			

CONS-H-S	F1815/WW/RS	CONVERSION OF SIMULATED IRREGULAR COMPONENT DATA TO ACTUAL SIMULATED DATA					
Month	Period	E't	St	Bo	B1	Y't	Y't(Trunc,0)
Jan-96	1	24.7602	11.3109	10.675	0.4463	47	47
Feb-96	2	22.7602	-4.1500	10.675	0.8927	30	30
Mar-96	3	16.7602	-11.9118	10.675	1.3390	17	17
Apr-96	4	24.7602	-7.5197	10.675	1.7853	30	30
May-96	5	6.7602	-11.1190	10.675	2.2317	9	9
Jun-96	6	0.7602	7.7917	10.675	2.6780	22	22
Jul-96	7	17.7602	-5.2446	10.675	3.1243	26	26
Aug-96	8	6.7602	0.7560	10.675	3.5707	22	22
Sep-96	9	1.7602	-0.3004	10.675	4.0170	16	16
Oct-96	10	11.7602	5.8039	10.675	4.4633	33	33
Nov-96	11	27.7602	-1.2500	10.675	4.9097	42	42
Dec-96	12	0.7602	3.2821	10.675	5.3560	20	20
Jan-97	13	4.7602	11.3109	10.675	5.8023	33	33
Feb-97	14	2.7602	-4.1500	10.675	6.2487	16	16
Mar-97	15	0.7602	-11.9118	10.675	6.6950	6	6
Apr-97	16	24.7602	-7.5197	10.675	7.1413	35	35
May-97	17	12.7602	-11.1190	10.675	7.5877	20	20
Jun-97	18	8.7602	7.7917	10.675	8.0340	35	35
Jul-97	19	-0.2398	-5.2446	10.675	8.4803	14	14
Aug-97	20	11.7602	0.7560	10.675	8.9267	32	32
Sep-97	21	17.7602	-0.3004	10.675	9.3730	38	38
Oct-97	22	3.7602	5.8039	10.675	9.8193	30	30
Nov-97	23	10.7602	-1.2500	10.675	10.2657	30	30
Dec-97	24	2.7602	3.2821	10.675	10.7120	27	27

Summary Statistics		Model	DV: TREND	Coefficients
Mean	0.0000	Bo	(Constant)	211.6852
Standard Deviation	82.2461	B1	PERIOD	3.1913
Minimum	-154.5145	Excel Formula=Rnguniform(min,max)		
Maximum	154.5145			
Count	24			

CONS-H-C	MS24665-134	CONVERSION OF SIMULATED IRREGULAR COMPONENT DATA TO ACTUAL SIMULATED DATA					
Month	Period	E't	St	Bo	B1	Y't	Y't(Trunc,0)
Jan-96	1	-71.4507	12.0128	211.685	3.1913	155	155
Feb-96	2	-20.7114	-142.7167	211.685	6.3826	55	55
Mar-96	3	0.0608	0.7426	211.685	9.5740	222	222
Apr-96	4	44.3666	-123.2544	211.685	12.7653	146	146
May-96	5	58.6669	38.4583	211.685	15.9566	325	325
Jun-96	6	-106.1414	75.8007	211.685	19.1479	200	200
Jul-96	7	5.8559	-87.8188	211.685	22.3393	152	152
Aug-96	8	97.1899	-69.2381	211.685	25.5306	265	265
Sep-96	9	-23.2413	85.5066	211.685	28.7219	303	303
Oct-96	10	-124.5950	64.9926	211.685	31.9132	184	184
Nov-96	11	-136.4780	-95.1917	211.685	35.1046	15	15
Dec-96	12	-26.2745	32.7853	211.685	38.2959	256	256
Jan-97	13	63.0084	12.0128	211.685	41.4872	328	328
Feb-97	14	-114.5490	-142.7167	211.685	44.6785	-1	0
Mar-97	15	-54.6496	0.7426	211.685	47.8699	206	206
Apr-97	16	134.5054	-123.2544	211.685	51.0612	274	274
May-97	17	-55.8526	38.4583	211.685	54.2525	249	249
Jun-97	18	63.8119	75.8007	211.685	57.4438	409	409
Jul-97	19	51.2767	-87.8188	211.685	60.6352	236	236
Aug-97	20	-63.4104	-69.2381	211.685	63.8265	143	143
Sep-97	21	4.8571	85.5066	211.685	67.0178	369	369
Oct-97	22	-132.9049	64.9926	211.685	70.2091	214	214
Nov-97	23	144.5118	-95.1917	211.685	73.4005	334	334
Dec-97	24	-54.5762	32.7853	211.685	76.5918	266	266

Summary Statistics		Model	DV: TREND	Coefficients
Mean	0.0000	Bo	(Constant)	4.986
Standard Deviation	5.9916	B1	PERIOD	0.061
Minimum	-4.1469	Excel Formula=Rnguniform(min,max)		
Maximum	4.1469			
Count	24			

REP-H-C	ZP650-SC-M-B-3	CONVERSION OF SIMULATED IRREGULAR COMPONENT DATA TO ACTUAL SIMULATED DATA					
Month	Period	E't	St	Bo	B1	Y't	Y't(Trunc,0)
Jan-96	1	-2.8438	1.4712	4.986	0.0610	4	4
Feb-96	2	-2.7697	-4.0083	4.986	0.1220	-2	0
Mar-96	3	-3.8143	-8.6005	4.986	0.1831	-7	0
Apr-96	4	-3.6402	-3.4254	4.986	0.2441	-2	0
May-96	5	-1.8681	1.8155	4.986	0.3051	5	5
Jun-96	6	0.8642	8.3967	4.986	0.3661	15	15
Jul-96	7	-4.0499	-4.5163	4.986	0.4271	-3	0
Aug-96	8	-2.9801	9.2798	4.986	0.4882	12	12
Sep-96	9	3.6304	-10.7303	4.986	0.5492	-2	0
Oct-96	10	0.4555	10.9681	4.986	0.6102	17	17
Nov-96	11	-3.6520	-0.9250	4.986	0.6712	1	1
Dec-96	12	-1.8005	-12.5353	4.986	0.7323	-9	0
Jan-97	13	1.5556	1.4712	4.986	0.7933	9	9
Feb-97	14	2.2656	-4.0083	4.986	0.8543	4	4
Mar-97	15	0.1426	-8.6005	4.986	0.9153	-3	0
Apr-97	16	0.1307	-3.4254	4.986	0.9763	3	3
May-97	17	0.0424	1.8155	4.986	1.0374	8	8
Jun-97	18	3.5453	8.3967	4.986	1.0984	18	18
Jul-97	19	2.1936	-4.5163	4.986	1.1594	4	4
Aug-97	20	-2.8003	9.2798	4.986	1.2204	13	13
Sep-97	21	2.2728	-10.7303	4.986	1.2814	-2	0
Oct-97	22	3.9994	10.9681	4.986	1.3425	21	21
Nov-97	23	0.3699	-0.9250	4.986	1.4035	6	6
Dec-97	24	2.2079	-12.5353	4.986	1.4645	-4	0

Summary Statistics		Model	DV: TREND	Coefficients
Mean	0.0000	Bo	(Constant)	1.8236
Standard Deviation	4.7417	B1	PERIOD	0.0662
Minimum	-2.0128	**Excel Formula=Rnguniform(min,max)**		
Maximum	2.0128			
Count	24			

REP-H-S	2-1517	CONVERSION OF SIMULATED IRREGULAR COMPONENT DATA TO ACTUAL SIMULATED DATA					
Month	**Period**	**E't**	**St**	**Bo**	**B1**	**Y't**	**Y't(Trunc,0)**
Jan-96	1	1.1878	1.4712	1.824	0.0662	5	5
Feb-96	2	1.0818	-4.0083	1.824	0.1324	-1	0
Mar-96	3	-1.8462	-8.6005	1.824	0.1986	-8	0
Apr-96	4	-0.6016	-3.4254	1.824	0.2647	-2	0
May-96	5	-1.3184	1.8155	1.824	0.3309	3	3
Jun-96	6	-0.6302	8.3967	1.824	0.3971	10	10
Jul-96	7	-1.3188	-4.5163	1.824	0.4633	-4	0
Aug-96	8	1.5205	9.2798	1.824	0.5295	13	13
Sep-96	9	-0.8419	-10.7303	1.824	0.5957	-9	0
Oct-96	10	-1.6447	10.9681	1.824	0.6618	12	12
Nov-96	11	-1.5702	-0.9250	1.824	0.7280	0	0
Dec-96	12	1.7582	-12.5353	1.824	0.7942	-8	0
Jan-97	13	1.1880	1.4712	1.824	0.8604	5	5
Feb-97	14	-1.8822	-4.0083	1.824	0.9266	-3	0
Mar-97	15	1.5696	-8.6005	1.824	0.9928	-4	0
Apr-97	16	-0.5803	-3.4254	1.824	1.0590	-1	0
May-97	17	0.3618	1.8155	1.824	1.1251	5	5
Jun-97	18	0.5513	8.3967	1.824	1.1913	12	12
Jul-97	19	1.2571	-4.5163	1.824	1.2575	0	0
Aug-97	20	1.0818	9.2798	1.824	1.3237	14	14
Sep-97	21	1.9471	-10.7303	1.824	1.3899	-6	0
Oct-97	22	0.4338	10.9681	1.824	1.4561	15	15
Nov-97	23	0.3484	-0.9250	1.824	1.5222	3	3
Dec-97	24	-0.4169	-12.5353	1.824	1.5884	-10	0

Summary Statistics		Model	DV: TREND	Coefficients
Mean	0.0000	Bo	(Constant)	1.6802
Standard Devi	4.5798	B1	PERIOD	-0.0274
Minimum	-1.9387	Excel Formula=Rnguniform(min,max)		
Maximum	1.9387			
Count	24			

REP-L-C	622-2362-001	CONVERSION OF SIMULATED IRREGULAR COMPONENT DATA TO ACTUAL SIMULATED DATA					
Month	Period	E't	St	Bo	B1	Y't	Y't(Trunc,0)
Jan-96	1	-1.0566	1.4712	1.680	-0.0274	2	2
Feb-96	2	1.3280	-4.0083	1.680	-0.0549	-1	0
Mar-96	3	-0.7635	-8.6005	1.680	-0.0823	-8	0
Apr-96	4	-0.1233	-3.4254	1.680	-0.1098	-2	0
May-96	5	0.1788	1.8155	1.680	-0.1372	4	4
Jun-96	6	-1.8920	8.3967	1.680	-0.1647	8	8
Jul-96	7	-1.7315	-4.5163	1.680	-0.1921	-5	0
Aug-96	8	-1.0540	9.2798	1.680	-0.2196	10	10
Sep-96	9	-0.6516	-10.7303	1.680	-0.2470	-10	0
Oct-96	10	1.5463	10.9681	1.680	-0.2745	14	14
Nov-96	11	-0.0216	-0.9250	1.680	-0.3019	0	0
Dec-96	12	-0.5177	-12.5353	1.680	-0.3294	-12	0
Jan-97	13	-0.8174	1.4712	1.680	-0.3568	2	2
Feb-97	14	-0.4763	-4.0083	1.680	-0.3843	-3	0
Mar-97	15	1.5633	-8.6005	1.680	-0.4117	-6	0
Apr-97	16	0.1706	-3.4254	1.680	-0.4391	-2	0
May-97	17	-0.0561	1.8155	1.680	-0.4666	3	3
Jun-97	18	0.2107	8.3967	1.680	-0.4940	10	10
Jul-97	19	-0.6799	-4.5163	1.680	-0.5215	-4	0
Aug-97	20	0.1487	9.2798	1.680	-0.5489	11	11
Sep-97	21	1.4398	-10.7303	1.680	-0.5764	-8	0
Oct-97	22	-1.3826	10.9681	1.680	-0.6038	11	11
Nov-97	23	-0.1779	-0.9250	1.680	-0.6313	0	0
Dec-97	24	1.0860	-12.5353	1.680	-0.6587	-10	0

Summary Statistics		Model	DV: TREND	Coefficients
Mean	0.0000	Bo	(Constant)	0.3968
Standard Deviation	4.9774	B1	PERIOD	0.0442
Minimum	-3.3137	Excel Formula=Rnguniform(min,max)		
Maximum	3.3137			
Count	24			

REP-L-S	DH1030-24-600CS	CONVERSION OF SIMULATED IRREGULAR COMPONENT DATA TO ACTUAL SIMULATED DATA					
Month	Period	E't	St	Bo	B1	Y't	Y't(Trunc,0)
Jan-96	1	-1.8580	1.4712	0.397	0.0442	0	0
Feb-96	2	3.0796	-4.0083	0.397	0.0884	0	0
Mar-96	3	-2.7727	-8.6005	0.397	0.1327	-11	0
Apr-96	4	1.9458	-3.4254	0.397	0.1769	-1	0
May-96	5	1.7350	1.8155	0.397	0.2211	4	4
Jun-96	6	0.8895	8.3967	0.397	0.2653	10	10
Jul-96	7	-2.5570	-4.5163	0.397	0.3096	-6	0
Aug-96	8	2.3757	9.2798	0.397	0.3538	12	12
Sep-96	9	-2.8807	-10.7303	0.397	0.3980	-13	0
Oct-96	10	-1.7003	10.9681	0.397	0.4422	10	10
Nov-96	11	-2.5478	-0.9250	0.397	0.4864	-3	0
Dec-96	12	-0.4923	-12.5353	0.397	0.5307	-12	0
Jan-97	13	3.0682	1.4712	0.397	0.5749	6	6
Feb-97	14	0.2013	-4.0083	0.397	0.6191	-3	0
Mar-97	15	-2.8776	-8.6005	0.397	0.6633	-10	0
Apr-97	16	1.2905	-3.4254	0.397	0.7076	-1	0
May-97	17	-3.2473	1.8155	0.397	0.7518	0	0
Jun-97	18	-2.0546	8.3967	0.397	0.7960	8	8
Jul-97	19	-1.2629	-4.5163	0.397	0.8402	-5	0
Aug-97	20	-0.1987	9.2798	0.397	0.8845	10	10
Sep-97	21	2.3131	-10.7303	0.397	0.9287	-7	0
Oct-97	22	1.8289	10.9681	0.397	0.9729	14	14
Nov-97	23	-1.1438	-0.9250	0.397	1.0171	-1	0
Dec-97	24	-0.5077	-12.5353	0.397	1.0613	-12	0

Appendix H: Comparison of Actual Demand Versus Simulated Demand

COMPARISON OF ACTUAL DATA AND SIMULATED DATA (PAIRED T-TEST)				
P/N 307 CONS-L-C Month	Historical Data Obs (Yt)	Model Data Sim (Y't)	Observed Difference dj	Squared Deviation From Mean $(dj-d^{\wedge})^2$
Jan-96	25	29	-4	12883.46
Feb-96	2	18	-16	10224.87
Mar-96	2	0	2	14191.97
Apr-96	0	6	-6	12333.01
May-96	3	3	0	13807.62
Jun-96	4	4	0	13743.18
Jul-96	0	8	-8	12003.01
Aug-96	17	20	-3	12976.61
Sep-96	18	28	-10	11518.39
Oct-96	7	6	1	14072.86
Nov-96	6	12	-6	12415.06
Dec-96	9	13	-4	12839.59
Jan-97	0	9	-9	11597.02
Feb-97	0	4	-4	12837.40
Mar-97	2	0	2	14191.97
Apr-97	2	8	-6	12373.93
May-97	0	5	-5	12474.64
Jun-97	2	0	2	14191.97
Jul-97	1	7	-6	12263.87
Aug-97	0	17	-17	10019.82
Sep-97	3	11	-8	11991.98
Oct-97	0	0	0	13719.45
Nov-97	0	0	0	13719.45
Dec-97	2	16	-14	10711.43
		Sum	-117.13004	**303102.55**

H_0 : The two populations are different

S^2d	13178.3717
d^	-4.8804
T statistics (To)	0.0018
α=	0.05
N=	24
$t_{0.05/2,k-1}$	2.3979 (critical value)
Reject H_0?	Yes (to< t(a,N-1))

COMPARISON OF ACTUAL DATA AND SIMULATED DATA (PAIRED T-TEST)				
F1815/WW/RS CONS-H-S Month	Historical Data Obs (Yt)	Model Data Sim (Y't)	Observed Difference dj	Squared Deviation From Mean $(dj-d^{\wedge})^2$
Jan-96	34	47	-13	63027.54
Feb-96	2	30	-28	55727.83
Mar-96	0	17	-17	61198.28
Apr-96	0	30	-30	55011.12
May-96	0	9	-9	65381.20
Jun-96	19	22	-3	68298.82
Jul-96	0	26	-26	56610.84
Aug-96	26	22	4	72083.37
Sep-96	11	16	-5	67129.45
Oct-96	20	33	-13	63273.80
Nov-96	20	42	-22	58636.83
Dec-96	29	20	9	74622.96
Jan-97	16	33	-17	61353.73
Feb-97	20	16	4	72205.83
Mar-97	6	6	0	69710.18
Apr-97	17	35	-18	60608.77
May-97	10	20	-10	64689.58
Jun-97	30	35	-5	67072.93
Jul-97	22	14	8	74296.76
Aug-97	7	32	-25	57181.94
Sep-97	20	38	-18	60879.41
Oct-97	26	30	-4	67697.19
Nov-97	13	30	-17	60907.48
Dec-97	17	27	-10	64422.58
		Sum	-264.24540	**1542028.39**

H_0 : The two populations are different

S^2d	67044.7128	
d^	-11.0102	
T statistics (To)	0.0008	
α=	0.05	
N=	24	
$t_{0.05/2,k-1}$	2.3979	(critical value)
Reject H_0?	Yes	(to< t(a,N-1))

COMPARISON OF ACTUAL DATA AND SIMULATED DATA (PAIRED T-TEST)				
MS24665-134 CONS-H-C Month	Historical Data Obs (Yt)	Model Data Sim (Y't)	Observed Difference dj	Squared Deviation From Mean $(dj-d^\wedge)^2$
Jan-96	257	155	102	45907.49
Feb-96	104	55	49	71001.71
Mar-96	245	222	23	85781.19
Apr-96	0	146	-146	212875.51
May-96	236	325	-89	163692.01
Jun-96	369	200	169	21701.46
Jul-96	0	152	-152	218914.71
Aug-96	306	265	41	75619.08
Sep-96	351	303	48	71553.04
Oct-96	325	184	141	30561.24
Nov-96	215	15	200	13442.49
Dec-96	278	256	22	86620.45
Jan-97	222	328	-106	178096.87
Feb-97	85	0	85	53278.65
Mar-97	251	206	45	73153.87
Apr-97	257	274	-17	110768.54
May-97	328	249	79	55868.48
Jun-97	284	409	-125	194096.04
Jul-97	322	236	86	52716.10
Aug-97	42	143	-101	173626.23
Sep-97	337	369	-32	121026.28
Oct-97	326	214	112	41535.95
Nov-97	146	334	-188	254245.30
Dec-97	336	266	70	60667.47
		Sum	315.82168	**2466750.15**

H_0 : The two populations are different

S^2d	107250.0065	
d^	13.1592	
T statistics (To)	0.0006	
$\alpha=$	0.05	
N=	24	
$t_{0.05/2'k-1}$	2.3979	(critical value)
Reject H_0?	**Yes**	(to< t(a,N-1))

COMPARISON OF ACTUAL DATA AND SIMULATED DATA (PAIRED T-TEST)				
ZP650-SC-M-B-3 REP-H-C Month	Historical Data Obs (Yt)	Model Data Sim (Y't)	Observed Difference dj	Squared Deviation From Mean $(dj\text{-}d^\wedge)^2$
Jan-96	5	4	1	96.98
Feb-96	2	0	2	110.72
Mar-96	2	0	2	110.72
Apr-96	0	0	0	72.63
May-96	1	5	-4	18.35
Jun-96	3	15	-12	9.55
Jul-96	0	0	0	72.63
Aug-96	8	12	-4	22.54
Sep-96	11	0	11	381.12
Oct-96	9	17	-8	0.25
Nov-96	8	1	7	238.45
Dec-96	16	0	16	601.34
Jan-97	17	9	8	279.42
Feb-97	8	4	4	154.37
Mar-97	0	0	0	72.63
Apr-97	3	3	0	78.40
May-97	1	8	-7	2.69
Jun-97	4	18	-14	30.30
Jul-97	6	4	2	114.48
Aug-97	2	13	-11	4.68
Sep-97	0	0	0	72.63
Oct-97	9	21	-12	14.24
Nov-97	8	6	2	114.22
Dec-97	7	0	7	240.94
		Sum	-8.52228	**2914.28**

H_0 : The two populations are different

S^2d	126.7079	
$d^\wedge$	-0.3551	
T statistics (To)	0.0137	
$\alpha=$	0.05	
N=	24	
$t_{0.05/2'k-1}$	2.3979	(critical value)
Reject H_0?	Yes	(to< t(a,N-1))

COMPARISON OF ACTUAL DATA AND SIMULATED DATA (PAIRED T-TEST)				
2-1517 REP-H-S Month	Historical Data Obs (Yt)	Model Data Sim (Y't)	Observed Difference dj	Squared Deviation From Mean $(dj-d^{\wedge})^2$
Jan-96	4	5	-1	1159.37
Feb-96	4	0	4	1489.83
Mar-96	1	0	1	1267.24
Apr-96	0	0	0	1197.04
May-96	1	3	-2	1085.48
Jun-96	5	10	-5	876.81
Jul-96	0	0	0	1197.04
Aug-96	0	13	-13	459.88
Sep-96	5	0	5	1568.02
Oct-96	4	12	-8	717.67
Nov-96	1	0	1	1263.22
Dec-96	2	0	2	1339.43
Jan-97	0	5	-5	855.86
Feb-97	1	0	1	1267.24
Mar-97	3	0	3	1413.63
Apr-97	2	0	2	1339.43
May-97	4	5	-1	1120.39
Jun-97	3	12	-9	657.17
Jul-97	3	0	3	1413.63
Aug-97	1	14	-13	487.94
Sep-97	6	0	6	1648.22
Oct-97	3	15	-12	525.17
Nov-97	3	3	0	1213.06
Dec-97	5	0	5	1568.02
		Sum	-34.59827	**27130.81**

H_0 : The two populations are different

S^2d	1179.6005	
$d^{\wedge}$	-1.4416	
T statistics (To)	0.0060	
$\alpha=$	0.05	
N=	24	
$t_{0.05/2,k-1}$	2.3979	(critical value)
Reject H_0?	Yes	(to< t(a,N-1))

COMPARISON OF ACTUAL DATA AND SIMULATED DATA (PAIRED T-TEST)				
622-2362-001 REP-L-C Month	Historical Data Obs (Yt)	Model Data Sim (Y't)	Observed Difference dj	Squared Deviation From Mean $(dj-d^{\wedge})^2$
Jan-96	1	2	-1	1811.44
Feb-96	1	0	1	1991.69
Mar-96	3	0	3	2174.20
Apr-96	0	0	0	1903.43
May-96	2	4	-2	1771.66
Jun-96	2	8	-6	1414.37
Jul-96	0	0	0	1903.43
Aug-96	2	10	-8	1291.82
Sep-96	0	0	0	1903.43
Oct-96	1	14	-13	942.99
Nov-96	1	0	1	1953.35
Dec-96	2	0	2	2081.94
Jan-97	0	2	-2	1734.82
Feb-97	4	0	4	2268.46
Mar-97	7	0	7	2563.23
Apr-97	1	0	1	1991.69
May-97	0	3	-3	1652.86
Jun-97	0	10	-10	1144.79
Jul-97	0	0	0	1903.43
Aug-97	0	11	-11	1093.53
Sep-97	1	0	1	1991.69
Oct-97	1	11	-10	1153.72
Nov-97	1	0	1	1991.69
Dec-97	0	0	0	1903.43
		Sum	-43.62833	**42537.09**

H_0 : The two populations are different

S^2d	1849.4387	
d^	-1.8178	
T statistics (To)	0.0048	
α=	0.05	
N=	24	
$t_{0.05/2,k-1}$	2.3979	(critical value)
Reject H_0?	Yes	(to< t(a,N-1))

COMPARISON OF ACTUAL DATA AND SIMULATED DATA (PAIRED T-TEST)				
DH1030-24-600CS REP-L-S Month	Historical Data Obs (Yt)	Model Data Sim (Y't)	Observed Difference dj	Squared Deviation From Mean $(dj-d^{\wedge})^2$
Jan-96	0	0	0	2830.75
Feb-96	2	0	2	3053.55
Mar-96	0	0	0	2836.51
Apr-96	0	0	0	2836.51
May-96	0	4	-4	2409.88
Jun-96	0	10	-10	1875.81
Jul-96	0	0	0	2836.51
Aug-96	0	12	-12	1668.96
Sep-96	0	0	0	2836.51
Oct-96	6	10	-4	2415.93
Nov-96	1	0	1	2944.03
Dec-96	0	0	0	2836.51
Jan-97	0	6	-6	2279.86
Feb-97	0	0	0	2836.51
Mar-97	1	0	1	2944.03
Apr-97	0	0	0	2836.51
May-97	1	0	1	2944.03
Jun-97	5	8	-3	2572.92
Jul-97	0	0	0	2836.51
Aug-97	2	10	-8	2015.70
Sep-97	0	0	0	2836.51
Oct-97	0	14	-14	1528.20
Nov-97	0	0	0	2836.51
Dec-97	3	0	3	3165.07
		Sum	-53.25893	**63013.84**

H_0 : The two populations are different

S^2d	2739.7321	
$d^{\wedge}$	-2.2191	
T statistics (To)	0.0040	
$\alpha=$	0.05	
N=	24	
$t_{0.05/2,k-1}$	2.3979	(critical value)
Reject H_0?	Yes	(to< t(a,N-1))

Appendix I: Desired Number of Replication for The Simulation Model

Part Number 61-0478-9
Forecasting Method: Single Exponential

Goal: Error of +- 0.05 mean

R = 30
alpha = 0.05

R_i	MAD_i
1	8.78
2	9.24
3	9.07
4	9.06
5	8.01
6	9.21
7	8.79
8	9.76
9	8.36
10	10.31
11	9.35
12	10.06
13	9.87
14	9.62
15	6.65
16	10.03
17	9.29
18	10.10
19	10.27
20	7.74
21	8.63
22	9.20
23	8.52
24	7.97
25	8.89
26	8.00
27	9.38
28	9.21
29	8.24
30	10.05

Avg-MAD = 9.0560 note: Avg-MAD = sum(MAD_i)/R
S_a^2 = 0.745 note: S_a^2 = sum(MAD_i-Avg_{MAD})^2/(R-1)
S_a^2/R = 0.025 note: var = S_a^2/R
std dev = 0.158 note: std dev = $(S_a^2/R)^{0.5}$

Confidence interval: avga +,- t(alpha/2, R-1) * std dev
Using Excel function Tinv, t 2.05

	LCL		Mean		UCL
and so	8.734	<=	9.06	<=	9.378

confidence interval is +,- 0.322

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?
Assumption: sample variance won't change much!
note: epsilon = $(t_{alpha/2, R-1})$(std dev) = $(t_{alpha/2, R-1})$*S/$(R^{0.5})$
so.. $R^{0.5} = t_{(alpha/2, R-1)}$*S/epsilon, and so R = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

Let Ro be the sample of 30replications already made, and let 0.745
Hence, S_a 0.8632
So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

R	$t_{(alpha/2,R-1)}$	X
30	2.05	15.203
20	2.09	15.922
17	2.12	16.333

Epsilon 5%: 0.45

Hence, perform about R-Ro =
R_0 = 30
R = 17
$R-R_0$ = -13

Part Number 61-0478-9
Forecasting Method: Double Exponential

Goal: Error of +- 0.05 mean

R = 30
alpha = 0.05

R_i	MAD_i
1	20.92
2	20.41
3	21.08
4	19.87
5	20.71
6	20.80
7	20.62
8	21.56
9	20.33
10	21.96
11	21.21
12	20.97
13	20.85
14	21.74
15	21.38
16	20.78
17	20.97
18	20.84
19	21.16
20	19.58
21	20.85
22	21.00
23	21.19
24	20.76
25	20.45
26	20.81
27	21.28
28	20.67
29	21.51
30	21.59

Avg-MAD = 20.9282 note: Avg-MAD = sum(MAD_i)/R
S_a^2 = 0.261 note: S_a^2 = sum(MAD_i-Avg_{MAD})^2/(R-1)
S_a^2/R = 0.009 note: var = S_a^2/R
std dev = 0.093 note: std dev = $(S_a^2/R)^{0.5}$

Confidence interval: avga +,- t(alpha/2, R-1) * std dev
Using Excel function Tin 2.05

	LCL		Mean	
and so	20.737	<=	20.93	<=

confidence interval is +,- 0.191

How many additional replications are needed to obtain a 95% confiden interval half length (epsilon) of +,- epsilon of MAD?
Assumption: sample variance won't change much!
note: epsilon = $(t_{alpha/2, R-1})$(std dev) = $(t_{alpha/2, R-1})$*S/$(R^{0.5})$
so.. $R^{0.5} = t_{(alpha/2, R-1)}$*S/epsilon, and so R = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

Let Ro be the sample of30 replications already made, 0.261
Hence, S 0.5108
So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

R	$t_{(alpha/2,R-1)}$	X
30	2.05	0.997
15	2.14	1.096
4	3.18	2.413

Epsilon 5%: 1.05

Hence, perform about R-Ro =
R_0 = 30
R = 4
$R-R_0$ = -26

Part Number 61-0478-9
Forecasting Method: Moving Average

Goal: Error of +- 0.05 mean

R = 30
alpha = 0.05

R_i	MAD_i
1	7.66
2	7.50
3	7.71
4	8.05
5	7.00
6	7.48
7	7.65
8	8.44
9	7.07
10	8.27
11	7.60
12	8.54
13	8.25
14	7.84
15	5.81
16	8.19
17	7.60
18	8.90
19	8.55
20	6.54
21	7.35
22	7.35
23	7.41
24	6.65
25	7.51
26	6.64
27	8.08
28	7.96
29	6.87
30	8.31

Avg-MAD = 7.6251 note: Avg-MAD = sum(MAD_i)/R
S_a^2 = 0.485 note: S_a^2 = sum(MAD_i-Avg_{MAD})^2/(R-1)
S_a^2/R = 0.016 note: var = S_a^2/R
std dev = 0.127 note: std dev = $(S_a^2/R)^{0.5}$

Confidence interval: avga +,- t(alpha/2, R-1) * std dev
Using Excel function Tinv 2.05

	LCL		Mean		UCL
and so	7.365	<=	7.63	<=	7.885

confidence interval is +,- 0.260

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?
Assumption: sample variance won'tchange much!
note: epsilon = $(t_{alpha/2, R-1})$(std dev) = $(t_{alpha/2, R-1})$*S/$(R^{0.5})$
so.. $R^{0.5} = t_{(alpha/2, R-1)}$*S/epsilon, and so R = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

Let Ro be the sample of30 replications already made, and 0.485
Hence, S_a 0.6962
So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2, R-1)}$*S/epsilon$^2)$

R	$t_{(alpha/2,R-1)}$	X
30	2.05	13.949
20	2.09	14.608
16	2.13	15.149

Epsilon 5%: 0.38

Hence, perform about R-Ro =
R_0 = 30
R = 16
$R-R_0$ = -14

Part Number 61-0478-9
Forecasting Method: Autoregression

Goal: Error of +- 0.05 mean

R = 30
alpha = 0.05

R_i	MAD_i
1	12.29
2	11.68
3	11.94
4	11.09
5	11.22
6	11.43
7	11.83
8	12.41
9	11.77
10	12.71
11	12.01
12	12.31
13	11.79
14	11.78
15	12.19
16	12.04
17	11.49
18	12.34
19	11.90
20	10.80
21	12.42
22	12.01
23	11.62
24	11.87
25	11.41
26	11.94
27	12.32
28	12.08
29	12.48
30	12.30

Avg-MAD = 11.9170 note: Avg-MAD = sum(MAD_i)/R
S_a^2 = 0.196 note: S_a^2 = sum(MAD_i-Avg_{MAD})^2/(R-1)
S_a^2/R = 0.007 note: var = S_a^2/R
std dev = 0.081 note: std dev = $(S_a^2/R)^{0.5}$

Confidence interval: avga +,- t(alpha/2, R-1) * std dev
Using Excel function Tin 2.05

	LCL		Mean	
and so	11.752	<=	11.92	<=

confidence interval is +,- 0.165

How many additional replications are needed to obtain a 95% confiden interval half length (epsilon) of +,- epsilon of MAD?
Assumption: sample variance won't change much!
note: epsilon = $(t_{alpha/2, R-1})$(std dev) = $(t_{alpha/2, R-1})$*S/$(R^{0.5})$
so.. $R^{0.5} = t_{(alpha/2, R-1)}$*S/epsilon, and so R = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

Let Ro be the sample of30 replications already made 0.196
Hence, S 0.4425
So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2, R-1)}$*S/epsilon$^2)$

R	$t_{(alpha/2,R-1)}$	X
30	2.05	2.306
15	2.14	2.536
6	2.57	3.644

Epsilon 5%: 0.60

Hence, perform about R-Ro =
R_0 = 30
R = 6
$R-R_0$ = -24

Part Number: 307

Forecasting Method: Single Exponential

Goal: Error of +- 0.05 mean

R_i	MAD_i
1	2.72
2	1.91
3	2.19
4	2.27
5	1.71
6	2.91
7	1.63
8	2.62
9	2.12
10	2.65
11	1.41
12	2.35
13	1.72
14	1.97
15	1.21
16	2.22
17	1.69
18	3.19
19	2.13
20	2.50
21	2.38
22	1.79
23	3.03
24	2.85
25	1.12
26	2.53
27	1.79
28	1.72
29	2.42
30	2.22

R = 30

alpha = 0.05

Confidence interval: avga +,- t(alpha/2, R-1) * std dev

Using Excel function Ti 2.05

LCL		Mean		UCL
and so 1.969	<=	2.17	<=	2.363

confidence interval is +,- 0.197

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?

Assumption: sample variance won't change much!

note: epsilon = $(t_{(alpha/2, R-1)})$(std dev) = $(t_{(alpha/2, R-1)})$*S/$(R^{0.5})$

so.. $R^{0.5} = t_{(alpha/2, R-1)}$*S/epsilon, and so R = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

Let Ro be the sample of30 replications already mad 0.278

Hence, 0.5277

So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

R	$t_{(a/2, R-1)}$	X
30	2.05	99.318
70	1.99	94.494
95	1.99	93.604

Epsilon 5%$^{1/2}$
0.11

Hence, perform about R-Ro =

R_o= 30

R= 95

$R-R_o$= 65

Avg-MAD = 2.1659 note: Avg-MAD = sum(MAD_i)/R

S_a^2= 0.278 note: S_a^2 = sum(MAD_i-Avg_{MAD})^2/(R-1)

S_a^2/R= 0.009 note: var = S_a^2/R

std dev = 0.096 note: std dev = $(S_a^2/R)^{0.5}$

Part Number: 307

Forecasting Method: Double Exponential

Goal: Error of +- 0.05 mean

R_i	MAD_i
1	3.23
2	2.14
3	2.49
4	2.79
5	2.04
6	3.39
7	1.86
8	3.15
9	2.45
10	3.28
11	1.80
12	2.72
13	2.03
14	2.38
15	1.43
16	2.77
17	1.87
18	3.80
19	2.46
20	2.95
21	2.73
22	1.97
23	3.33
24	3.23
25	1.34
26	2.86
27	2.19
28	2.16
29	2.90
30	2.52

R = 30

alpha = 0.05

Confidence interval: avga +,- t(alpha/2, R-1) * std dev

Using Excel function Ti 2.05

LCL		Mean		UCL
and so 2.314	<=	2.54	<=	2.770

confidence interval is +,- 0.228

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?

Assumption: sample variance won'tchange much!

note: epsilon = $(t_{(alpha/2, R-1)})$(std dev) = $(t_{(alpha/2, R-1)})$*S/$(R^{0.5})$

so.. $R^{0.5} = t_{(alpha/2, R-1)}$*S/epsilon, and so R = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

Let Ro be the sample of 30 replications already made 0.373

Hence, 0.6106

So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

R	$t_{(a/2, R-1)}$	X
30	2.05	96.523
70	1.99	91.835
93	1.99	91.021

Epsilon 5%$^{1/2}$
0.13

Hence, perform about R-Ro =

R_o= 30

R= 93

$R-R_o$= 63

Avg-MAD = 2.5421 note: Avg-MAD = sum(MAD_i)/R

S_a^2= 0.373 note: S_a^2 = sum(MAD_i-Avg_{MAD})^2/(R-1)

S_a^2/R= 0.012 note: var = S_a^2/R

std dev = 0.111 note: std dev = $(S_a^2/R)^{0.5}$

Part Number: 307

Forecasting Method: Moving Average

Goal: Error of +- 0.05 mean

R_i	MAD_i
1	2.65
2	1.97
3	2.08
4	2.42
5	1.85
6	2.88
7	1.62
8	2.87
9	2.24
10	2.72
11	1.32
12	2.39
13	1.55
14	2.18
15	1.30
16	2.37
17	1.86
18	3.19
19	2.10
20	2.39
21	2.41
22	1.86
23	2.83
24	2.84
25	1.13
26	2.79
27	1.77
28	1.70
29	2.47
30	2.36

R = 30

alpha = 0.05

Confidence interval: avga +,- t(alpha/2, R-1) * std dev

Using Excel function Tin 2.05

LCL		Mean		UCL
and so 2.006	<=	2.20	<=	2.402

confidence interval is +,- 0.198

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?

Assumption: sample variance won't change much!

note: epsilon = $(t_{(alpha/2, R-1)})$(std dev) = $(t_{(alpha/2, R-1)})$*S/$(R^{0.5})$

so.. $R^{0.5} = t_{(alpha/2, R-1)}$*S/epsilon, and so R = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

Let Ro be the sample of 30 replications already made, 0.281

Hence, S 0.5300

So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

R	$t_{(a/2, R-1)}$	X
30	2.05	96.743
70	1.99	92.044
93	1.99	91.228

Epsilon 5%$^{1/2}$
0.11

Hence, perform about R-Ro =

R_o= 30

R= 93

$R-R_o$= 63

Avg-MAD = 2.2040 note: Avg-MAD = sum(MAD_i)/R

S_a^2= 0.281 note: S_a^2 = sum(MAD_i-Avg_{MAD})^2/(R-1)

S_a^2/R= 0.009 note: var = S_a^2/R

std dev = 0.097 note: std dev = $(S_a^2/R)^{0.5}$

Part Number

Forecasting Method: Autoregression

Goal: Error of +- 0.05 mean

R_i	MAD_i
1	2.90
2	2.57
3	2.20
4	2.72
5	2.41
6	2.97
7	1.88
8	2.77
9	2.59
10	3.82
11	1.95
12	2.74
13	2.10
14	3.35
15	1.66
16	2.93
17	2.25
18	4.27
19	2.67
20	2.76
21	2.69
22	2.11
23	2.82
24	2.77
25	1.78
26	2.38
27	2.76
28	2.23
29	2.67
30	2.65

R = 30

alpha = 0.05

Confidence interval: avge +,- t(alpha/2, R-1) * std dev

Using Excel function T 2.05

LCL		Mean		UCL
and so 2.406	<=	2.61	<=	2.819

confidence interval is +,- 0.207

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?

Assumption: sample variance won't change much!

note: epsilon = $(t_{(alpha/2, R-1)})$(std dev) = $(t_{(alpha/2, R-1)})$*S/$(R^{0.5})$

so.. $R^{0.5} = t_{(alpha/2, R-1)}$*S/epsilon, and so R = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

Let Ro be the sample of 30 replications already made, 0.306

Hence, S 0.5533

So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2, R-1)}$*S/epsilon$^2)$

R	$t_{(a/2, R-1)}$	X
30	2.05	75.068
50	2.01	72.473
72	1.99	71.350

Epsilon 5%$^{1/2}$
0.13

Hence, perform about R-Ro =

R_o= 30

R= 72

$R-R_o$= 42

Avg-MAD = 2.6122 note: Avg-MAD = sum(MAD_i)/R

S_a^2= 0.306 note: S_a^2 = sum(MAD_i-Avg_{MAD})^2/(R-1)

S_a^2/R= 0.010 note: var = S_a^2/R

std dev = 0.101 note: std dev = $(S_a^2/R)^{0.5}$

Part Number: F1815/WW/RS

Forecasting Method: Single Exponential

Goal: Error of +- 0.05 mean

R_i	MAD_i
1	10.04
2	9.85
3	10.13
4	10.83
5	8.43
6	11.18
7	9.81
8	11.08
9	11.41
10	11.93
11	8.15
12	10.98
13	10.95
14	11.55
15	12.49
16	8.95
17	10.77
18	10.69
19	10.96
20	8.53
21	8.85
22	9.52
23	10.42
24	11.10
25	10.27
26	10.57
27	9.59
28	8.32
29	9.54
30	10.01

Avg-MAD = 10.2293 note: Avg-MAD = sum(MAD_i)/R

S_a^2 = 1.228 note: S_a^2 = sum(MAD_i-Avg_{MAD})^2/(R-1)

S_a^2/R = 0.041 note: var = S_a^2/R

std dev = 0.202 note: std dev = $(S_a^2/R)^{0.5}$

R = 30

alpha = 0.05

Confidence interval: avga +,- t(alpha/2, R-1) * std dev

Using Excel function Tinv, 2.05

	LCL		Mean		UCL
and so	9.816	<=	10.23	<=	10.643

confidence interval is +,- 0.414

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?

Assumption: sample variance won't change much!

note: epsilon = $(t_{(alpha/2, R-1)})$(std dev) = $(t_{(alpha/2, R-1)})$*S/$(R^{0.5})$

so.. $R^{0.5} = t_{(alpha/2, R-1)}$*S/epsilon, and so R = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

Let Ro be the sample of 30 replications already made, 1.228

Hence, S_a 1.1079

So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

R	$t_{(.025, R-1)}$	X
30	2.05	19.629
25	2.06	19.989
21	2.09	20.418

Epsilon 5%[1]: 0.51

Hence, perform about R-Ro =

R_o = 30

R = 21

$R-R_o$ = -9

Part Number: F1815/WW/RS

Forecasting Method: Double Exponential

Goal: Error of +- 0.05 mean

R_i	MAD_i
1	57.71
2	53.58
3	58.58
4	59.67
5	54.78
6	60.42
7	53.64
8	60.45
9	64.31
10	64.84
11	48.09
12	63.42
13	61.36
14	65.46
15	66.12
16	54.59
17	60.55
18	55.34
19	61.34
20	44.11
21	49.65
22	52.59
23	57.56
24	64.40
25	60.90
26	54.55
27	55.78
28	47.91
29	51.38
30	59.30

Avg-MAD = 57.4119 note: Avg-MAD = sum(MAD_i)/R

S_a^2 = 32.503 note: S_a^2 = sum(MAD_i-Avg_{MAD})^2/(R-1)

S_a^2/R = 1.083 note: var = S_a^2/R

std dev = 1.041 note: std dev = $(S_a^2/R)^{0.5}$

R = 30

alpha = 0.05

Confidence interval: avga +,- t(alpha/2, R-1) * std dev

Using Excel function Tinv, t_i 2.05

	LCL		Mean		UCL
and so	55.283	<=	57.41	<=	59.541

confidence interval is +,- 2.129

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?

Assumption: sample variancewon't change much!

note: epsilon = $(t_{(alpha/2, R-1)})$(std dev) = $(t_{(alpha/2, R-1)})$*S/$(R^{0.5})$

so.. $R^{0.5} = t_{(alpha/2, R-1)}$*S/epsilon, and so R = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

Let Ro be the sample of30 replications already made, and let S_a^2 = S_a^2 = 32.503

Hence, S_a = 5.7011

So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

R	$t_{(.025, R-1)}$	X
30	2.05	16.499
25	2.06	16.802
19	2.10	17.410

Epsilon 5%[1]: 2.87

Hence, perform about R-Ro =

R_o = 30

R = 19

$R-R_o$ = -11

Part Number: F1815/WW/RS

Forecasting Method: Moving Average

Goal: Error of +- 0.05 mean

R_i	MAD_i
1	9.19
2	10.02
3	10.17
4	11.53
5	8.10
6	10.23
7	9.82
8	10.48
9	11.10
10	11.53
11	7.82
12	10.67
13	11.07
14	10.64
15	12.27
16	8.85
17	10.15
18	10.62
19	10.40
20	8.41
21	9.23
22	10.10
23	10.93
24	10.72
25	10.16
26	10.40
27	9.38
28	8.84
29	9.61
30	10.08

Avg-MAD = 10.0838 note: Avg-MAD = sum(MAD_i)/R

S_a^2 = 1.058 note: S_a^2 = sum(MAD_i-Avg_{MAD})^2/(R-1)

S_a^2/R = 0.035 note: var = S_a^2/R

std dev = 0.188 note: std dev = $(S_a^2/R)^{0.5}$

R = 30

alpha = 0.05

Confidence interval: avga +,- t(alpha/2, R-1) * std dev

Using Excel function Tinv, t 2.05

	LCL		Mean		UCL
and so	9.700	<=	10.08	<=	10.468

confidence interval is +,- 0.384

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?

Assumption: sample variance won't change much!

note: epsilon = $(t_{(alpha/2, R-1)})$(std dev) = $(t_{(alpha/2, R-1)})$*S/$(R^{0.5})$

so.. $R^{0.5} = t_{(alpha/2, R-1)}$*S/epsilon, and so R = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

Let Ro be the sample of30 replications already made, and let S_a^2 = S_a^2 = 1.058

Hence, S_a = 1.0287

So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

R	$t_{(.025, R-1)}$	X
30	2.05	17.414
25	2.06	17.733
19	2.10	18.375

Epsilon 5%[1]: 0.50

Hence, perform about R-Ro =

R_o = 30

R = 19

$R-R_o$ = -11

Part Number: F1815/WW/RS

Forecasting Method: Autoregression

Goal: Error of +- 0.05 mean

R_i	MAD_i
1	13.26
2	12.70
3	12.14
4	13.29
5	10.45
6	13.09
7	12.35
8	12.45
9	13.78
10	13.68
11	10.82
12	13.03
13	12.92
14	12.63
15	13.35
16	12.30
17	11.51
18	12.56
19	12.84
20	11.34
21	9.68
22	12.46
23	12.35
24	12.48
25	11.84
26	11.90
27	11.49
28	11.03
29	11.13
30	13.27

Avg-MAD = 12.2715 note: Avg-MAD = sum(MAD_i)/R

S_a^2 = 0.977 note: S_a^2 = sum(MAD_i-Avg_{MAD})^2/(R-1)

S_a^2/R = 0.033 note: var = S_a^2/R

std dev = 0.180 note: std dev = $(S_a^2/R)^{0.5}$

R = 30

alpha = 0.05

Confidence interval: avga +,- t(alpha/2, R-1) * std dev

Using Excel function Tinv, 2.05

	LCL		Mean	
and so	11.902	<=	12.27	<=

confidence interval is +,- 0.369

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?

Assumption: sample variance won't change much!

note: epsilon = $(t_{(alpha/2, R-1)})$(std dev) = $(t_{(alpha/2, R-1)})$*S/$(R^{0.5})$

so.. $R^{0.5} = t_{(alpha/2, R-1)}$*S/epsilon, and so R = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

Let Ro be the sample of30 replications already made, and let S_a^2 = S_a^2 = 0.977

Hence, S_a 0.9886

So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

R	$t_{(.025, R-1)}$	X
30	2.05	10.858
15	2.14	11.941
14	2.16	12.115

Epsilon 5%[1]: 0.61

Hence, perform about R-Ro =

R_o = 30

R = 14

$R-R_o$ = -16

Part Number: MS24665-134

Forecasting Method: Single Exponential

Goal: Error of + - 0.05 mean

R_i	MAD_i
1	90.44
2	86.00
3	78.27
4	101.97
5	72.91
6	78.62
7	67.98
8	85.37
9	96.26
10	84.21
11	93.30
12	94.70
13	86.02
14	79.69
15	85.28
16	83.81
17	80.48
18	69.11
19	113.22
20	97.67
21	82.22
22	70.27
23	86.81
24	77.65
25	87.11
26	85.07
27	84.54
28	88.02
29	75.99
30	78.85

R = 30

alpha = 0.05

Confidence interval: avga +,- t(alpha/2, R-1) * std dev

Using Excel function Tinv, 2.05

	LCL		Mean		UCL
and so	81.057	<=	84.73	<=	88.401

confidence interval is +,- 3.672

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?

Assumption: sample variance won't change much!

note: epsilon = $(t_{(alpha/2, R-1)})$(std dev) = $(t_{(alpha/2, R-1)})$*S/$(R^{0.5})$

so.. $R^{0.5} = t_{(alpha/2, R-1)}$*S/epsilon, and so R = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

Let Ro be the sample of 30 replications already made, and let $S_o^2 = S_s^2$ = 96.697

Hence, S_o 9.8335

So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2,R-1)}$*S/epsilon$)^2$

R	$t_{(alpha/2,R-1)}$	X
30	2.05	22.537
28	2.05	22.683
25	2.06	22.950

Epsilon 5%[1]: 4.24

Hence, perform about R-Ro =

R_o= 30

R= 25

$R-R_o$= -5

Avg-MAD = 84.7286 note: Avg-MAD = sum(MAD_i)/R

S_s^2= 96.697 note: S_s^2 = sum(MAD_i-$Avg_{MAD})^2$/(R-1)

S_s^2/R= 3.223 note: var = S_s^2/R

std dev = 1.795 note: std dev = $(S_s^2/R)^{0.5}$

Part Number: MS24665-134

Forecasting Method: Double Exponential

Goal: Error of + - 0.05 mean

R_i	MAD_i
1	119.69
2	109.96
3	109.48
4	132.72
5	96.11
6	97.16
7	94.31
8	118.58
9	119.61
10	110.74
11	121.62
12	120.07
13	106.76
14	96.23
15	118.63
16	102.38
17	109.05
18	84.30
19	148.27
20	125.97
21	108.03
22	97.61
23	119.64
24	99.42
25	111.46
26	105.88
27	113.00
28	114.97
29	100.85
30	107.41

R = 30

alpha = 0.05

Confidence interval: avga +,- t(alpha/2, R-1) * std dev

Using Excel function Tinv, t_i 2.05

	LCL		Mean		UCL
and so	105.848	<=	110.66	<=	115.479

confidence interval is +,- 4.815

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?

Assumption: sample variance won't change much!

note: epsilon = $(t_{(alpha/2, R-1)})$(std dev) = $(t_{(alpha/2, R-1)})$*S/$(R^{0.5})$

so.. $R^{0.5} = t_{(alpha/2, R-1)}$*S/epsilon, and so R = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

Let Ro be the sample of 30 replications already made, and let $S_o^2 = S_s^2$ = 166.304

Hence, S_o = 12.8959

So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2,R-1)}$*S/epsilon$)^2$

R	$t_{(alpha/2,R-1)}$	X
30	2.05	22.722
28	2.05	22.868
25	2.06	23.138

Epsilon 5%[1]: 5.53

Hence, perform about R-Ro =

R_o= 30

R= 25

$R-R_o$= -5

Avg-MAD = 110.6635 note: Avg-MAD = sum(MAD_i)/R

S_s^2= 166.304 note: S_s^2 = sum(MAD_i-$Avg_{MAD})^2$/(R-1)

S_s^2/R= 5.543 note: var = S_s^2/R

std dev = 2.354 note: std dev = $(S_s^2/R)^{0.5}$

Part Number: MS24665-134

Forecasting Method: Moving Average

Goal: Error of + - 0.05 mean

R_i	MAD_i
1	85.33
2	90.31
3	77.34
4	98.59
5	73.26
6	77.58
7	66.08
8	84.60
9	93.14
10	78.76
11	99.09
12	96.35
13	90.01
14	79.59
15	81.85
16	86.17
17	80.07
18	71.75
19	112.88
20	90.96
21	83
22	69.45
23	85.49
24	81.81
25	81.00
26	79.39
27	82.21
28	89.89
29	75.90
30	78.82

R = 30

alpha = 0.05

Confidence interval: avga +,- t(alpha/2, R-1) * std dev

Using Excel function Tinv, 2.05

	LCL		Mean		UCL
and so	80.393	<=	84.04	<=	87.679

confidence interval is +,- 3.643

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?

Assumption: sample variance won't change much!

note: epsilon = $(t_{(alpha/2, R-1)})$(std dev) = $(t_{(alpha/2, R-1)})$*S/$(R^{0.5})$

so.. $R^{0.5} = t_{(alpha/2, R-1)}$*S/epsilon, and so R = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

Let Ro be the sample of 30 replications already made, and let $S_o^2 = S_s^2$ = 95.174

Hence, S_o = 9.7557

So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2,R-1)}$*S/epsilon$)^2$

R	$t_{(alpha/2,R-1)}$	X
30	2.05	22.549
25	2.06	22.963
24	2.07	23.069

Epsilon 5%[1]: 4.20

Hence, perform about R-Ro =

R_o= 30

R= 24

$R-R_o$= -6

Avg-MAD = 84.0363 note: Avg-MAD = sum(MAD_i)/R

S_s^2= 95.174 note: S_s^2 = sum(MAD_i-$Avg_{MAD})^2$/(R-1)

S_s^2/R= 3.172 note: var = S_s^2/R

std dev = 1.781 note: std dev = $(S_s^2/R)^{0.5}$

Part Number: MS24665-134

Forecasting Method: Autoregression

Goal: Error of + - 0.05 mean

R_i	MAD_i
1	115.24
2	112.70
3	125.58
4	118.70
5	97.50
6	128.98
7	114.27
8	118.78
9	129.18
10	102.57
11	135.13
12	125.11
13	147.57
14	148.80
15	116.14
16	131.10
17	126.83
18	132.57
19	124.36
20	124.94
21	125
22	143.10
23	116.78
24	122.48
25	109.21
26	112.86
27	137.47
28	123.10
29	143.83
30	146.77

R = 30

alpha = 0.05

Confidence interval: avga +,- t(alpha/2, R-1) * std dev

Using Excel function Tinv, t_i 2.05

	LCL		Mean		UCL
and so	120.390	<=	125.23	<=	130.070

confidence interval is +,- 4.840

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?

Assumption: sample variance won't change much!

note: epsilon = $(t_{(alpha/2, R-1)})$(std dev) = $(t_{(alpha/2, R-1)})$*S/$(R^{0.5})$

so.. $R^{0.5} = t_{(alpha/2, R-1)}$*S/epsilon, and so R = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

Let Ro be the sample of 30 replications already made, and let $S_o^2 = S_s^2$ = 168.012

Hence, S_o = 12.9619

So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2,R-1)}$*S/epsilon$)^2$

R	$t_{(alpha/2,R-1)}$	X
30	2.05	17.925
25	2.06	18.254
20	2.09	18.773

Epsilon 5%[1]: 6.26

Hence, perform about R-Ro =

R_o= 30

R= 20

$R-R_o$= -10

Avg-MAD = 125.2300 note: Avg-MAD = sum(MAD_i)/R

S_s^2= 168.012 note: S_s^2 = sum(MAD_i-$Avg_{MAD})^2$/(R-1)

S_s^2/R= 5.600 note: var = S_s^2/R

std dev = 2.367 note: std dev = $(S_s^2/R)^{0.5}$

Part Number: ZP650-SC-M-B-3
Forecasting Method: Single Exponential

Goal: Error of +- 0.05 mean

R_i	MAD_i
1	6.28
2	6.26
3	5.93
4	6.18
5	6.57
6	6.75
7	6.42
8	5.70
9	5.93
10	6.54
11	5.55
12	5.83
13	5.41
14	6.05
15	5.91
16	6.28
17	6.60
18	5.92
19	6.36
20	5.83
21	5.82
22	6.23
23	5.65
24	6.10
25	6.14
26	5.55
27	5.39
28	6.01
29	5.81
30	5.76

R = 30
alpha = 0.05

Confidence interval: avga +,- t(alpha/2, R-1) * std dev
Using Excel function Tinv, t 2.05

	LCL		Mean		UCL
and so	5.892	<=	6.03	<=	6.159

confidence interval is +,- 0.133

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?

Assumption: sample variance won't change much!

note: epsilon = $(t_{(alpha/2,\ R-1)})$(std dev) = $(t_{(alpha/2,\ R)})$*S/$(R^{0.5})$

so.. $R^{0.5} = t_{(alpha/2,\ R-1)}$*S/epsilon, and so R = $(t_{(alpha/2,\ R-1)}$*S/epsilon$)^2$

Let Ro be the sample of30 replications already made, and let $S_o^2 = S_a^2$ = 0.128

Hence, S_o = 0.3574

So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2,R-1)}$*S/epsilon$)^2$

R	$t_{(alpha/2,R-1)}$	X
30	2.05	5.888
15	2.14	6.475
9	2.31	7.485

Epsilon 5%: 0.30

Hence, perform about R-Ro =
Ro= 30
R= 9
R-Ro= -21

Avg-MAD = 6.0252 note: Avg-MAD = sum(MAD)/R
S_a^2= 0.128 note: S_a^2 = sum$(MAD_i-Avg_{MAD})^2$/(R-1)
S_a^2/R= 0.004 note: var = S_a^2/R
std dev = 0.065 note: std dev = $(S_a^2/R)^{0.5}$

Part Number: ZP650-SC-M-B-3
Forecasting Method: Double Exponential

Goal: Error of +- 0.05 mean

R_i	MAD_i
1	8.36
2	8.62
3	8.21
4	7.99
5	8.45
6	8.38
7	8.39
8	8.16
9	8.11
10	7.68
11	7.33
12	7.95
13	7.91
14	7.67
15	7.87
16	8.36
17	8.44
18	8.00
19	7.89
20	8.07
21	7.93
22	7.86
23	7.85
24	8.41
25	7.91
26	8.10
27	7.58
28	8.12
29	8.00
30	7.73

R = 30
alpha = 0.05

Confidence interval: avga +,- t(alpha/2, R-1) * std dev
Using Excel function Tinv, t 2.05

	LCL		Mean		UCL
and so	7.934	<=	8.04	<=	8.156

confidence interval is +,- 0.111

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?

Assumption: sample variance won't change much!

note: epsilon = $(t_{(alpha/2,\ R-1)})$(std dev) = $(t_{(alpha/2,\ R)})$*S/$(R^{0.5})$

so.. $R^{0.5} = t_{(alpha/2,\ R-1)}$*S/epsilon, and so R = $(t_{(alpha/2,\ R-1)}$*S/epsilon$)^2$

Let Ro be the sample of30 replications already made, and let $S_o^2 = S_a^2$ = 0.089

Hence, S_o = 0.2975

So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2,R-1)}$*S/epsilon$)^2$

R	$t_{(alpha/2,R-1)}$	X
30	2.05	2.289
15	2.14	2.517
5	2.78	4.218

Epsilon 5%: 0.40

Hence, perform about R-Ro =
Ro= 30
R= 5
R-Ro= -25

Avg-MAD = 8.0450 note: Avg-MAD = sum(MAD)/R
S_a^2= 0.089 note: S_a^2 = sum$(MAD-Avg_{MAD})^2$/(R-1)
S_a^2/R= 0.003 note: var = S_a^2/R
std dev = 0.054 note: std dev = $(S_a^2/R)^{0.5}$

Part Number: ZP650-SC-M-B-3
Forecasting Method: Moving Average

Goal: Error of +- 0.05 mean

R_i	MAD_i
1	6.88
2	6.83
3	6.76
4	6.77
5	7.25
6	7.21
7	7.05
8	6.32
9	6.39
10	7.00
11	6.19
12	6.46
13	5.86
14	6.76
15	6.44
16	6.88
17	7.03
18	6.34
19	7.13
20	6.34
21	6.32
22	6.75
23	6.19
24	7.03
25	6.57
26	6.26
27	5.88
28	6.65
29	6.63
30	6.32

R = 30
alpha = 0.05

Confidence interval: avga +,- t(alpha/2, R-1) * std dev
Using Excel function Tinv, 2.05

	LCL		Mean		UCL
and so	6.476	<=	6.62	<=	6.757

confidence interval is +,- 0.141

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?

Assumption: sample variance won't change much!

note: epsilon = $(t_{(alpha/2,\ R-1)})$(std dev) = $(t_{(alpha/2,\ R-1)})$*S/$(R^{0.5})$

so.. $R^{0.5} = t_{(alpha/2,\ R-1)}$*S/epsilon, and so R = $(t_{(alpha/2,\ R-1)}$*S/epsilon$)^2$

Let Ro be the sample of 30replications already made, and let $S_o^2 = S^2$ = 0.142

Hence, S_o = 0.3763

So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2,R-1)}$*S/epsilon$^2)$

R	$t_{(alpha/2,R-1)}$	X
30	2.05	5.413
15	2.14	5.953
8	2.36	7.236

Epsilon 5%: 0.33

Hence, perform about R-Ro =
R_o= 30
R= 8
R-R_o= -22

Avg-MAD = 6.6166 note: Avg-MAD = sum(MAD)/R
S_a^2= 0.142 note: S_a^2 = sum$(MAD-Avg_{MAD})^2$/(R-1)
S_a^2/R= 0.005 note: var = S_a^2/R
std dev = 0.069 note: std dev = $(S_a^2/R)^{0.5}$

Part Number: ZP650-SC-M-B-3
Forecasting Method: Autoregression

Goal: Error of +- 0.05 mean

R_i	MAD_i
1	8.92
2	8.37
3	8.24
4	8.48
5	9.23
6	9.36
7	8.86
8	7.49
9	8.38
10	9.33
11	7.50
12	8.25
13	7.81
14	8.73
15	8.53
16	8.92
17	9.06
18	8.35
19	9.46
20	8.67
21	8.18
22	8.11
23	8.06
24	8.47
25	8.95
26	8.53
27	7.86
28	8.11
29	7.98
30	8.06

R = 30
alpha = 0.05

Confidence interval: avga +,- t(alpha/2, R-1) * std dev
Using Excel function T 2.05

	LCL		Mean		UCL
and so	8.277	<=	8.47	<=	8.672

confidence interval is +,- 0.198

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?

Assumption: sample variance won't change much!

note: epsilon = $(t_{(alpha/2,\ R-1)})$(std dev) = $(t_{(alpha/2,\ R)})$*S/$(R^{0.5})$

so.. $R^{0.5} = t_{(alpha/2,\ R-1)}$*S/epsilon, and so R = $(t_{(alpha/2,\ R-1)}$*S/epsilon$)^2$

Let Ro be the sample of 30replications already made, and let $S_o^2 = S_a^2$ = 0.280

Hence, S_o = 0.5290

So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2,R-1)}$*S/epsilon$^2)$

R	$t_{(alpha/2,R-1)}$	X
30	2.05	6.519
15	2.14	7.169
9	2.31	8.287

Epsilon 5%: 0.42

Hence, perform about R-Ro =
R_o= 30
R= 9
R-R_o= -21

Avg-MAD = 8.4749 note: Avg-MAD = sum(MAD)/R
S_a^2= 0.280 note: S_a^2 = sum$(MAD-Avg_{MAD})^2$/(R-1)
S_a^2/R= 0.009 note: var = S_a^2/R
std dev = 0.097 note: std dev = $(S_a^2/R)^{0.5}$

Part Number: 2-1517

Forecasting Method: Single Exponential

Goal: Error of +- 0.05 mean

R = 30

alpha = 0.05

R_i	MAD_i
1	6.85
2	6.73
3	6.30
4	6.30
5	6.61
6	6.28
7	6.36
8	6.80
9	6.61
10	6.42
11	6.59
12	6.57
13	6.67
14	6.98
15	6.36
16	6.74
17	6.53
18	6.36
19	6.76
20	6.68
21	6.50
22	6.55
23	6.24
24	6.90
25	6.69
26	6.47
27	6.51
28	6.51
29	6.54
30	6.40

Avg-MAD = 6.5602 note: Avg-MAD = sum(MAD_i)/R

S_s^2= 0.037 note: S_s^2 = sum(MAD_i-Avg_{MAD})^2/(R-1)

S_s^2/R= 0.001 note: var = S_s^2/R

std dev = 0.035 note: std dev = $(S_s^2/R)^{0.5}$

Confidence interval: avga +,- t(alpha/2, R-1) * std dev

Using Excel function Ti **2.05**

	LCL		Mean		UCL
and so	6.488	<=	6.56	<=	6.632
confidence interval is +,-			0.072		

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?

Assumption: sample variance won't change much!

note: **epsilon** = $(t_{(alpha/2, R-1)})$(std dev) = $(t_{(alpha/2, R-1)})$*S/$(R^{0.5})$

so.. $R^{0.5}$ = $t_{(alpha/2, R-1)}$*S/epsilon, and so R = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

Let Ro be the sample of 30 replications already made, and let S_o^2 = S_s^2 = 0.037

Hence, S_o = 0.1925

So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2,R-1)}$*S/epsilon$)^2$

R	$t_{(alpha/2,R-1)}$	X
30	2.05	1.441
15	2.14	1.584
4	3.18	3.488

Epsilon 5%
0.33

Hence, perform about R-Ro =

R_o= 30

R= 4

R-R_o= -26

Part Number: 2-1517

Forecasting Method: Double Exponential

Goal: Error of +- 0.05 mean

R = 30

alpha = 0.05

R_i	MAD_i
1	6.53
2	6.40
3	5.99
4	6.05
5	6.28
6	6.06
7	6.02
8	6.49
9	6.28
10	6.09
11	6.28
12	6.24
13	6.35
14	6.60
15	6.03
16	6.42
17	6.26
18	6.11
19	6.41
20	6.38
21	6.18
22	6.24
23	6.00
24	6.56
25	6.36
26	6.12
27	6.17
28	6.28
29	6.29
30	6.03

Avg-MAD = 6.2502 note: Avg-MAD = sum(MAD_i)/R

S_s^2= 0.031 note: S_s^2 = sum(MAD_i-Avg_{MAD})^2/(R-1)

S_s^2/R= 0.001 note: var = S_s^2/R

std dev = 0.032 note: std dev = $(S_s^2/R)^{0.5}$

Confidence interval: avge +,- t(alpha/2, R-1) * std dev

Using Excel function **2.05**

	LCL		Mean		UCL
and so	6.184	<=	6.25	<=	6.316
confidence interval is +,-			0.066		

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?

Assumption: sample variance won't change much!

note: **epsilon** = $(t_{(alpha/2, R-1)})$(std dev) = $(t_{(alpha/2, R-1)})$*S/$(R^{0.5})$

so.. $R^{0.5}$ = $t_{(alpha/2, R-1)}$*S/epsilon, and so R = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

Let Ro be the sample of 30 replications already made, and let S_o^2 = S_s^2 = 0.031

Hence, S_o = 0.1769

So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2,R-1)}$*S/epsilon$)^2$

R	$t_{(alpha/2,R-1)}$	X
30	2.05	1.340
15	2.14	1.474
5	2.78	2.470

Epsilon 5%
0.31

Hence, perform about R-Ro =

R_o= 30

R= 5

R-R_o= -25

Part Number: 2-1517

Forecasting Method: Moving Average

Goal: Error of +- 0.05 mean

R = 30

alpha = 0.05

R_i	MAD_i
1	5.69
2	5.73
3	5.29
4	5.46
5	5.66
6	5.55
7	5.33
8	5.80
9	5.47
10	5.37
11	5.55
12	5.61
13	5.73
14	5.68
15	5.29
16	5.70
17	5.54
18	5.52
19	5.56
20	5.69
21	5.48
22	5.52
23	5.33
24	5.74
25	5.65
26	5.41
27	5.51
28	5.77
29	5.67
30	5.24

Avg-MAD = 5.5508 note: Avg-MAD = sum(MAD_i)/R

S_s^2= 0.025 note: S_s^2 = sum(MAD_i-Avg_{MAD})^2/(R-1)

S_s^2/R= 0.001 note: var = S_s^2/R

std dev = 0.029 note: std dev = $(S_s^2/R)^{0.5}$

Confidence interval: avga +,- t(alpha/2, R-1) * std dev

Using Excel function Ti **2.05**

	LCL		Mean		UCL
and so	5.491	<=	5.55	<=	5.610
confidence interval is +,-			0.059		

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?

Assumption: sample variance won't change much!

note: **epsilon** = $(t_{(alpha/2, R-1)})$(std dev) = $(t_{(alpha/2, R-1)})$*S/$(R^{0.5})$

so.. $R^{0.5}$ = $t_{(alpha/2, R-1)}$*S/epsilon, and so R = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

Let Ro be the sample of 30 replications already made, and let S_o^2 = S_s^2 = 0.025

Hence, S_o = 0.1592

So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2,R-1)}$*S/epsilon$)^2$

R	$t_{(alpha/2,R-1)}$	X
30	2.05	1.376
15	2.14	1.514
5	2.78	2.537

Epsilon 5%
0.28

Hence, perform about R-Ro =

R_o= 30

R= 5

R-R_o= -25

Part Number: 2-1517

Forecasting Method: Autoregression

Goal: Error of +- 0.05 mean

R = 30

alpha = 0.05

R_i	MAD_i
1	5.25
2	5.22
3	4.97
4	4.97
5	5.19
6	4.95
7	4.85
8	5.30
9	5.12
10	4.93
11	5.10
12	5.10
13	5.19
14	5.38
15	4.88
16	5.17
17	5.05
18	4.98
19	5.21
20	5.20
21	5.07
22	5.12
23	4.91
24	5.40
25	5.13
26	4.97
27	4.99
28	5.12
29	5.20
30	4.88

Avg-MAD = 5.0940 note: Avg-MAD = sum(MAD_i)/R

S_s^2= 0.022 note: S_s^2 = sum(MAD_i-Avg_{MAD})^2/(R-1)

S_s^2/R= 0.001 note: var = S_s^2/R

std dev = 0.027 note: std dev = $(S_s^2/R)^{0.5}$

Confidence interval: avga +,- t(alpha/2, R-1) * std dev

Using Excel function Tin **2.05**

	LCL		Mean		UCL
and so	5.039	<=	5.09	<=	5.149
confidence interval is +,-			0.055		

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?

Assumption: sample variance won't change much!

note: epsilon = $(t_{(alpha/2, R-1)})$(std dev) = $(t_{(alpha/2, R-1)})$*S/$(R^{0.5})$

so.. $R^{0.5}$ = $t_{(alpha/2, R-1)}$*S/epsilon, and so R = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

Let Ro be the sample of 30 replications already made, and let S_o^2 = S_s^2 = 0.022

Hence, S_o = 0.1472

So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2,R-1)}$*S/epsilon$)^2$

R	$t_{(alpha/2,R-1)}$	X
30	2.05	1.397
15	2.14	1.537
5	2.78	2.575

Epsilon 5%
0.25

Hence, perform about R-Ro =

R_o= 30

R= 5

R-R_o= -25

Part Number 622-2362-001

Forecasting Method: Single Exponential

Goal: Error of +- 0.05 mean

R = 30

alpha = 0.05

R_i	MAD_i
1	3.67
2	3.71
3	3.98
4	3.65
5	3.65
6	3.82
7	3.94
8	3.70
9	3.85
10	3.81
11	3.94
12	3.99
13	3.87
14	3.76
15	4.01
16	3.63
17	3.66
18	3.84
19	4.11
20	3.72
21	3.85
22	3.97
23	4.00
24	3.84
25	3.76
26	3.89
27	3.86
28	3.83
29	3.71
30	3.85

Confidence interval: avga +,- t(alpha/2, R-1) * std dev

Using Excel function **2.05**

	LCL		Mean		UCL
and so	3.782	<=	3.83	<=	3.877
confidence interval is +,-			0.048		

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?

Assumption: sample variance won't change much!

note: epsilon = $(t_{(alpha/2, R-1)})$(std dev) = $(t_{(alpha/2, R-1)})$*S/$(R^{0.5})$

so.. $R^{0.5} = t_{(alpha/2, R-1)}$*S/epsilon, and so R = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

Let Ro be the sample of 30 replications already made, and let $S_o^2 = S_a^2 =$ 0.016

Hence, $S_o =$ 0.1278

So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

R	$t_{(.025, R-1)}$	X
30	2.05	1.863
15	2.14	2.049
5	2.78	3.434

Epsilon 5%: 0.19

Hence, perform about R-Ro =

R_o= 30

R= 5

$R-R_o$= -25

Avg-MAD = 3.8295 note: Avg-MAD = sum(MAD_i)/R

S_a^2= 0.016 note: S_a^2 = sum(MAD_i-$Avg_{MAD}$$)^2$/(R-1)

S_a^2/R= 0.001 note: var = S_a^2/R

std dev = 0.023 note: std dev = $(S_a^2/R)^{0.5}$

Part Number 622-2362-001

Forecasting Method: Double Exponential

Goal: Error of +- 0.05 mean

R = 30

alpha = 0.05

R_i	MAD_i
1	6.62
2	6.66
3	7.29
4	6.47
5	6.64
6	6.68
7	7.04
8	6.61
9	6.87
10	7.00
11	7.17
12	7.11
13	6.87
14	6.92
15	7.20
16	6.54
17	6.57
18	6.77
19	7.28
20	6.85
21	6.80
22	7.08
23	7.21
24	6.90
25	6.78
26	6.77
27	6.87
28	7.01
29	6.83
30	6.81

Confidence interval: avga +,- t(alpha/2, R-1) * std dev

Using Excel function **2.05**

	LCL		Mean		UCL
and so	6.790	<=	6.87	<=	6.959
confidence interval is +,-			0.084		

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?

Assumption: sample variance won't change much!

note: epsilon = $(t_{(alpha/2, R-1)})$(std dev) = $(t_{(alpha/2, R-1)})$*S/$(R^{0.5})$

so.. $R^{0.5} = t_{(alpha/2, R-1)}$*S/epsilon, and so R = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

Let Ro be the sample of 30 replications already made, and let $S_o^2 = S_a^2 =$ 0.051

Hence, $S_o =$ 0.2261

So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

R	$t_{(.025, R-1)}$	X
30	2.05	1.809
15	2.14	1.990
5	2.78	3.335

Epsilon 5%: 0.34

Hence, perform about R-Ro =

R_o= 30

R= 5

$R-R_o$= -25

Avg-MAD = 6.8741 note: Avg-MAD = sum(MAD_i)/R

S_a^2= 0.051 note: S_a^2 = sum(MAD_i-$Avg_{MAD}$$)^2$/(R-1)

S_a^2/R= 0.002 note: var = S_a^2/R

std dev = 0.041 note: std dev = $(S_a^2/R)^{0.5}$

Part Number 622-2362-001

Forecasting Method: Moving Average

Goal: Error of +- 0.05 mean

R = 30

alpha = 0.05

R_i	MAD_i
1	3.90
2	4.01
3	4
4	3.91
5	3.90
6	4.12
7	4.28
8	3.99
9	4.14
10	4.09
11	4.21
12	4.34
13	4.13
14	3.97
15	4.28
16	3.91
17	3.96
18	4.17
19	4.39
20	4.01
21	4.15
22	4.24
23	4.33
24	4.16
25	4.03
26	4.20
27	4.16
28	4.11
29	3.93
30	4.13

Confidence interval: avga +,- t(alpha/2, R-1) * std dev

Using Excel function **2.05**

	LCL		Mean		UCL
and so	4.061	<=	4.11	<=	4.168
confidence interval is +,-			0.054		

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?

Assumption: sample variance won't change much!

note: epsilon = $(t_{(alpha/2, R-1)})$(std dev) = $(t_{(alpha/2, R-1)})$*S/$(R^{0.5})$

so.. $R^{0.5} = t_{(alpha/2, R-1)}$*S/epsilon, and so R = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

Let Ro be the sample of 30 replications already made, and let $S_o^2 = S_a^2 =$ 0.021

Hence, $S_o =$ 0.1437

So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

R	$t_{(.025, R-1)}$	X
30	2.05	2.042
15	2.14	2.245
5	2.78	3.762

Epsilon 5%: 0.21

Hence, perform about R-Ro =

R_o= 30

R= 5

$R-R_o$= -25

Avg-MAD = 4.1146 note: Avg-MAD = sum(MAD_i)/R

S_a^2= 0.021 note: S_a^2 = sum(MAD_i-$Avg_{MAD}$$)^2$/(R-1)

S_a^2/R= 0.001 note: var = S_a^2/R

std dev = 0.026 note: std dev = $(S_a^2/R)^{0.5}$

Part Number 622-2362-001

Forecasting Method: Autoregression

Goal: Error of +- 0.05 mean

R = 30

alpha = 0.05

R_i	MAD_i
1	3.39
2	3.43
3	4
4	3.25
5	3.46
6	3.42
7	3.58
8	3.40
9	3.54
10	3.61
11	3.73
12	3.51
13	3.49
14	3.58
15	3.71
16	3.30
17	3.40
18	3.32
19	3.82
20	3.45
21	3.56
22	3.61
23	3.62
24	3.43
25	3.44
26	3.50
27	3.49
28	3.62
29	3.52
30	3.59

Confidence interval: avga +,- t(alpha/2, R-1) * std dev

Using Excel function Ti **2.05**

	LCL		Mean		UCL
and so	3.465	<=	3.51	<=	3.560
confidence interval is +,-			0.048		

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?

Assumption: sample variance won't change much!

note: epsilon = $(t_{(alpha/2, R-1)})$(std dev) = $(t_{(alpha/2, R-1)})$*S/$(R^{0.5})$

so.. $R^{0.5} = t_{(alpha/2, R-1)}$*S/epsilon, and so R = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

Let Ro be the sample of 30 replications already made, and let $S_o^2 = S_a^2 =$ 0.016

Hence, $S_o =$ 0.1280

So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

R	$t_{(.025, R-1)}$	X
30	2.05	2.224
15	2.14	2.446
3	4.30	9.842

Epsilon 5%: 0.18

Hence, perform about R-Ro =

R_o= 30

R= 3

$R-R_o$= -27

Avg-MAD = 3.5124 note: Avg-MAD = sum(MAD_i)/R

S_a^2= 0.016 note: S_a^2 = sum(MAD_i-$Avg_{MAD}$$)^2$/(R-1)

S_a^2/R= 0.001 note: var = S_a^2/R

std dev = 0.023 note: std dev = $(S_a^2/R)^{0.5}$

Part Number: DH1030-24-600CS

Forecasting Method: Single Exponential

Goal: Error of +- 0.05 mean

R = 30

alpha = 0.05

R_i	MAD_i
1	4.60
2	4.93
3	4.85
4	4.46
5	4.94
6	5.25
7	5.41
8	4.45
9	5.07
10	4.81
11	5.37
12	4.76
13	4.63
14	5.14
15	4.59
16	4.68
17	4.53
18	4.89
19	4.58
20	4.81
21	4.61
22	5.03
23	5.36
24	5.02
25	4.95
26	4.79
27	4.85
28	5.04
29	5.44
30	4.75

Confidence interval: avga +,- t(alpha/2, R-1) * std dev

Using Excel function Ti 2.05

	LCL		Mean		UCL
and so	4.780	<=	4.89	<=	4.993

confidence interval is +,- 0.106

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?

Assumption: sample variance won't change much!

note: epsilon = $(t_{(alpha/2, R-1)})$(std dev) = $(t_{(alpha/2, R-1)})$*S/($R^{0.5}$)

so.. $R^{0.5} = t_{(alpha/2, R-1)}$*S/epsilon, and so R = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

Let Ro be the sample of 30 replications already made, and let $S_o^2 = S_s^2$ = 0.081

Hence, S_o = 0.2841

So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

R	t[illegible]	X
30	2.05	5.656
15	2.14	6.220
9	2.31	7.190

Epsilon 5%: 0.24

Hence, perform about R-Ro =

R_o= 30

R= 9

$R-R_o$= -21

Avg-MAD = 4.8865 note: Avg-MAD = sum(MAD_i)/R

S_s^2= 0.081 note: S_s^2 = sum(MAD_i-$Avg_{MAD}$$)^2$/(R-1)

S_s^2/R= 0.003 note: var = S_s^2/R

std dev = 0.052 note: std dev = $(S_s^2/R)^{0.5}$

Part Number: DH1030-24-600CS

Forecasting Method: Double Exponential

Goal: Error of +- 0.05 mean

R = 30

alpha = 0.05

R_i	MAD_i
1	4.06
2	4.60
3	4.09
4	4.10
5	4.33
6	4.28
7	4.97
8	4.07
9	4.42
10	4.10
11	4.76
12	4.18
13	4.15
14	4.42
15	3.97
16	4.15
17	3.92
18	4.16
19	4.08
20	4.10
21	3.89
22	4.39
23	4.54
24	4.42
25	4.26
26	4.11
27	4.10
28	4.55
29	4.69
30	4.08

Confidence interval: avga +,- t(alpha/2, R-1) * std dev

Using Excel function T 2.05

	LCL		Mean
and so	4.168	<=	4.27

confidence interval is +,- 0.098

How many additional replications are needed to obtain a 95% c interval half length (epsilon) of +,- epsilon of MAD?

Assumption: sample variance won't change much!

note: epsilon = $(t_{(alpha/2, R-1)})$(std dev) = $(t_{(alpha/2, R-1)})$*S/($R^{0.5}$)

so.. $R^{0.5} = t_{(alpha/2, R-1)}$*S/epsilon, and so R = $(t_{(alpha/2, R-1)}$*S/ep

Let Ro be the sample of 30 replications already made, and let $S_o^2 = S_s^2$ =

Hence, S_o = 0.2618

So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2, R-1)}$*S/epsilon

R	t[illegible]	X
30	2.05	6.304
15	2.14	6.933
9	2.31	8.014

Hence, perform about R-Ro =

R_o=

R=

$R-R_o$=

Avg-MAD = 4.2654 note: Avg-MAD = sum(MAD_i)/R

S_s^2= 0.069 note: S_s^2 = sum(MAD_i-$Avg_{MAD}$$)^2$/(R-1)

S_s^2/R= 0.002 note: var = S_s^2/R

std dev = 0.048 note: std dev = $(S_s^2/R)^{0.5}$

Part Number: DH1030-24-600CS

Forecasting Method: Moving Average

Goal: Error of +- 0.05 mean

R = 30

alpha = 0.05

R_i	MAD_i
1	4.67
2	4.76
3	4.74
4	4.37
5	4.90
6	5.14
7	5.32
8	4.49
9	5.07
10	4.67
11	5.33
12	4.65
13	4.52
14	5.07
15	4.55
16	4.48
17	4.32
18	4.64
19	4.49
20	4.70
21	4.57
22	4.94
23	5.21
24	5.03
25	4.90
26	4.79
27	4.77
28	4.95
29	5.52
30	4.66

Confidence interval: avga +,- t(alpha/2, R-1) * std dev

Using Excel function 2.05

	LCL		Mean		UCL
and so	4.695	<=	4.81	<=	4.919

confidence interval is +,- 0.112

How many additional replications are needed to obtain a 95% confidence interval half length (epsilon) of +,- epsilon of MAD?

Assumption: sample variance won't change much!

note: **epsilon** = $(t_{(alpha/2, R-1)})$(std dev) = $(t_{(alpha/2, R-1)})$*S/($R^{0.5}$)

so.. $R^{0.5} = t_{(alpha/2, R-1)}$*S/epsilon, and so R = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

Let Ro be the sample of 30 replications already made, and let $S_o^2 = S_s^2$ = 0.090

Hence, S_o = 0.3004

So, want to find R such that R>=Ro, and R >= X = $(t_{(alpha/2, R-1)}$*S/epsilon$)^2$

R	t[illegible]	X
30	2.05	6.535
15	2.14	7.186
9	2.31	8.307

Epsilon 5%: 0.24

Hence, perform about R-Ro =

R_o= 30

R= 9

$R-R_o$= -21

Avg-MAD = 4.8071 note: Avg-MAD = sum(MAD_i)/R

S_s^2= 0.090 note: S_s^2 = sum(MAD_i-$Avg_{MAD}$$)^2$/(R-1)

S_s^2/R= 0.003 note: var = S_s^2/R

std dev = 0.055 note: std dev = $(S_s^2/R)^{0.5}$

Part Number: DH1030-24-600CS

Forecasting Method: Autoregression

Goal: Error of +- 0.05 mean

R = 30

alpha = 0.05

R_i	MAD_i
1	3.94
2	4.42
3	3.93
4	3.85
5	4.02
6	4.03
7	4.69
8	3.83
9	4.20
10	3.91
11	4.48
12	4.07
13	3.99
14	4.16
15	3.77
16	3.90
17	3.80
18	4.01
19	3.83
20	3.87
21	3.81
22	4.18
23	4.25
24	4.16
25	4.02
26	3.92
27	3.87
28	4.38
29	4.37
30	3.82

Confidence interval: avga +,- t(alpha/2, R-1) *

Using Excel function Tinv, $t_{0.02}$ 2.05

	LCL	
and so	3.961	<=

confidence interval is +,-

How many additional replications are interval half length (epsilon) of +,- epsi

Assumption: sample variance won't change

note: **epsilon** = $(t_{(alpha/2, R-1)})$(std dev) = $(t_{alpha/2,}$

so.. $R^{0.5} = t_{(alpha/2, R-1)}$*S/epsilon, and

Let Ro be the sample of 30 replications alread

Hence, S_o = 0.2347

So, want to find R such that R>=Ro, and R

R	t[illegible]	X
30	2.05	5.620
15	2.14	6.180
10	2.26	6.875

Avg-MAD = 4.0491 note: Avg-MAD = sum(MAD_i)/R

S_s^2= 0.055 note: S_s^2 = sum(MAD_i-$Avg_{MAD}$$)^2$/(R-1)

S_s^2/R= 0.002 note: var = S_s^2/R

std dev = 0.043 note: std dev = $(S_s^2/R)^{0.5}$

Appendix J: Forecasting Errors Using Simulated Demand Data

CONS-L-S	61-04789																
ME	F1	F2	F3	F4	CFE	F1	F2	F3	F4	MAD	F1	F2	F3	F4	MSE	F1	F2
1	1	-21	1	11	1	24	-753	43	406	1	8.78	20.92	7.66	12.29	1	27.13	23.39
2	1	-20	1	11	2	24	-735	40	379	2	9.24	20.41	7.50	11.68	2	28.04	25.68
3	1	-21	1	11	3	18	-759	32	393	3	9.07	21.08	7.71	11.94	3	22.64	17.63
4	1	-20	1	10	4	26	-715	42	362	4	9.06	19.87	8.05	11.09	4	32.84	22.60
5	1	-21	1	11	5	22	-746	40	397	5	8.01	20.71	7.00	11.22	5	24.51	16.33
6	0	-21	1	11	6	15	-749	29	388	6	9.21	20.80	7.48	11.43	6	32.81	22.57
7	1	-21	1	11	7	28	-742	48	398	7	8.79	20.62	7.65	11.83	7	24.07	23.00
8	1	-22	1	11	8	21	-776	33	410	8	9.76	21.56	8.44	12.41	8	25.42	19.46
9	1	-20	1	11	9	32	-732	52	396	9	8.36	20.33	7.07	11.77	9	24.91	22.29
10	1	-22	1	12	10	19	-791	40	448	10	10.31	21.96	8.27	12.71	10	41.83	21.73
11	1	-21	1	12	11	19	-763	42	419	11	9.35	21.21	7.60	12.01	11	20.44	22.16
12	1	-21	1	11	12	23	-755	45	410	12	10.06	20.97	8.54	12.31	12	31.35	22.16
13	1	-21	1	11	13	19	-751	35	394	13	9.87	20.85	8.25	11.79	13	35.80	21.91
14	0	-22	1	12	14	13	-782	30	420	14	9.62	21.74	7.84	11.78	14	24.08	11.78
15	1	-21	1	12	15	29	-770	48	427	15	6.65	21.38	5.81	12.19	15	20.97	22.72
16	1	-21	1	11	16	19	-748	38	397	16	10.03	20.78	8.19	12.04	16	39.73	25.12
17	1	-21	1	11	17	22	-755	37	401	17	9.29	20.97	7.60	11.49	17	30.33	17.15
18	1	-21	1	11	18	21	-750	41	401	18	10.10	20.84	8.90	12.34	18	26.60	28.05
19	1	-21	1	12	19	19	-762	41	416	19	10.27	21.16	8.55	11.90	19	36.90	14.78
20	1	-20	1	10	20	23	-705	46	363	20	7.74	19.58	6.54	10.80	20	24.57	21.60
21	1	-21	1	12	21	28	-751	52	420	21	8.63	20.85	7.35	12.42	21	28.33	21.24
22	1	-21	1	11	22	22	-756	38	400	22	9.20	21.00	7.35	12.01	22	30.13	17.52
23	1	-21	1	11	23	26	-763	37	403	23	8.52	21.19	7.41	11.62	23	20.64	14.19
24	1	-21	1	11	24	24	-747	33	386	24	7.97	20.76	6.65	11.87	24	36.05	19.23
25	1	-20	1	11	25	21	-736	37	382	25	8.89	20.45	7.51	11.41	25	33.73	17.41
26	1	-21	1	11	26	19	-749	38	400	26	8.00	20.81	6.64	11.94	26	31.62	27.08
27	1	-21	1	12	27	26	-766	43	421	27	9.38	21.28	8.08	12.32	27	28.34	28.81
28	1	-21	1	11	28	22	-744	45	407	28	9.21	20.67	7.96	12.08	28	38.21	32.75
29	0	-22	1	12	29	18	-774	39	423	29	8.24	21.51	6.87	12.48	29	32.46	18.75
30	1	-22	1	12	30	19	-777	38	425	30	10.05	21.59	8.31	12.30	30	34.45	19.47
31	1	-21	1	12	31	30	-756	49	416	31	9.19	21.00	7.33	12.20	31	31.68	20.21
32	1	-21	1	11	32	26	-743	41	395	32	9.55	20.64	8.12	12.40	32	29.85	27.79
33	1	-21	1	12	33	32	-766	50	424	33	9.72	21.29	7.95	12.33	33	32.20	22.21
34	1	-21	1	12	34	22	-769	40	420	34	8.40	21.37	7.57	13.02	34	36.43	27.67
35	1	-20	1	11	35	23	-729	45	383	35	9.18	20.26	7.62	11.33	35	29.80	22.27
36	1	-21	1	11	36	28	-745	46	398	36	8.96	20.69	7.68	11.74	36	31.74	20.46
37	1	-21	1	11	37	18	-748	33	389	37	9.56	20.77	8.08	11.26	37	34.16	14.24
38	0	-23	1	13	38	13	-817	32	463	38	9.13	22.70	7.87	13.16	38	27.15	16.02
39	1	-20	1	11	39	28	-717	48	380	39	9.35	19.93	7.89	11.40	39	39.79	17.95
40	0	-21	1	10	40	10	-744	24	378	40	9.01	20.68	7.35	11.08	40	25.67	16.24
41	1	-21	1	11	41	21	-762	40	410	41	8.56	21.17	7.40	11.90	41	33.87	20.79
42	1	-21	1	11	42	18	-750	31	390	42	8.88	20.84	7.56	11.54	42	28.87	22.50
43	1	-21	1	11	43	25	-764	41	413	43	9.16	21.22	7.68	12.35	43	35.50	22.49
44	1	-20	1	10	44	19	-711	37	352	44	8.63	19.74	7.09	10.69	44	29.25	25.08
45	1	-20	1	10	45	28	-720	43	372	45	8.68	20.01	7.22	10.94	45	16.34	21.10
46	1	-20	1	10	46	22	-723	42	373	46	8.88	20.08	7.62	11.49	46	40.91	21.99
47	0	-20	1	9	47	11	-705	25	332	47	8.56	19.58	7.51	10.73	47	27.63	19.09
48	0	-21	1	11	48	12	-770	25	402	48	9.04	21.39	7.82	11.59	48	39.46	17.40
49	1	-20	1	11	49	18	-734	38	381	49	8.94	20.38	7.31	11.25	49	31.56	24.36
50	0	-21	1	11	50	17	-742	38	387	50	9.76	20.60	8.15	11.43	50	33.71	25.62
Average	0.62	-20.92	1.12	11.20	Average	22.47	-753.16	40.43	403.27	Average	9.08	20.92	7.63	11.94	Average	29.70	21.46

CONS-L-C	307

ME	F1	F2	F3	F4	CFE	F1	F2	F3	F4	MAD	F1	F2	F3	F4	MSE	F1	F2
1	0	0	0	1	1	-5	8	-7	22	1	2.72	3.23	2.65	2.90	1	11.19	15.37
2	0	0	0	0	2	-15	-7	-14	2	2	1.91	2.14	1.97	2.57	2	6.45	10.34
3	0	0	0	0	3	-7	2	-7	10	3	2.19	2.49	2.08	2.20	3	3.98	5.83
4	-1	0	-1	0	4	-24	-2	-29	13	4	2.27	2.79	2.42	2.72	4	10.02	13.98
5	0	0	0	0	5	-9	12	-13	-9	5	1.71	2.04	1.85	2.41	5	7.49	10.15
6	0	0	0	1	6	-3	7	-2	50	6	2.91	3.39	2.88	2.97	6	8.78	12.78
7	0	0	0	0	7	-12	1	-15	5	7	1.63	1.86	1.62	1.88	7	2.37	3.41
8	-1	0	-1	1	8	-20	-2	-26	28	8	2.62	3.15	2.87	2.77	8	7.33	9.91
9	-1	0	-1	0	9	-19	-7	-21	2	9	2.12	2.45	2.24	2.59	9	6.18	10.02
10	0	0	0	1	10	-11	4	-14	49	10	2.65	3.28	2.72	3.82	10	12.21	15.37
11	0	0	0	0	11	-1	7	-1	-15	11	1.41	1.80	1.32	1.95	11	4.87	6.35
12	-1	0	-1	1	12	-18	11	-24	22	12	2.35	2.72	2.39	2.74	12	7.78	10.54
13	0	1	0	0	13	-5	19	-7	-8	13	1.72	2.03	1.55	2.10	13	4.97	7.80
14	0	0	-1	1	14	-16	12	-19	31	14	1.97	2.38	2.18	3.35	14	8.40	10.76
15	0	0	0	-1	15	-9	9	-13	-29	15	1.21	1.43	1.30	1.66	15	2.10	2.69
16	-1	0	-1	1	16	-20	-7	-23	23	16	2.22	2.77	2.37	2.93	16	8.10	11.43
17	0	0	-1	0	17	-15	15	-20	-7	17	1.69	1.87	1.86	2.25	17	5.61	7.94
18	0	0	0	2	18	-14	-2	-16	85	18	3.19	3.80	3.19	4.27	18	11.80	16.18
19	-1	0	-1	1	19	-21	1	-23	21	19	2.13	2.46	2.10	2.67	19	4.93	6.90
20	0	0	0	1	20	-3	11	-4	21	20	2.50	2.95	2.39	2.76	20	6.95	10.03
21	0	0	0	0	21	-3	9	-2	15	21	2.38	2.73	2.41	2.69	21	7.14	10.67
22	0	0	0	0	22	-11	11	-14	-2	22	1.79	1.97	1.86	2.11	22	3.42	5.17
23	-1	0	-1	1	23	-20	3	-22	40	23	3.03	3.33	2.83	2.82	23	8.92	13.89
24	0	0	-1	1	24	-16	-6	-19	42	24	2.85	3.23	2.84	2.77	24	7.76	12.06
25	0	0	0	-1	25	-5	13	-7	-28	25	1.12	1.34	1.13	1.78	25	3.04	4.42
26	-1	0	-1	1	26	-23	-8	-27	21	26	2.53	2.86	2.79	2.38	26	4.72	8.48
27	0	0	0	0	27	-8	14	-10	8	27	1.79	2.19	1.77	2.76	27	7.77	10.54
28	0	0	0	0	28	-4	9	-7	-15	28	1.72	2.16	1.70	2.23	28	6.97	9.12
29	0	1	0	0	29	-10	19	-16	12	29	2.42	2.90	2.47	2.67	29	11.72	16.27
30	0	0	0	0	30	-12	0	-15	17	30	2.22	2.52	2.36	2.65	30	7.07	10.24
31	0	0	0	0	31	-5	5	-6	-2	31	1.52	1.80	1.61	2.25	31	5.01	6.76
32	0	0	0	1	32	-12	10	-16	33	32	2.98	3.39	2.95	2.83	32	10.28	14.77
33	0	0	0	1	33	-14	3	-17	35	33	2.86	3.42	2.87	3.28	33	11.03	14.71
34	0	0	0	2	34	-14	4	-17	57	34	3.14	3.56	3.31	3.11	34	8.05	11.82
35	0	0	0	1	35	-4	7	-5	38	35	2.68	3.10	2.51	2.93	35	7.54	10.97
36	0	0	0	-1	36	-5	16	-6	-19	36	1.49	1.87	1.46	2.04	36	4.60	6.49
37	-1	0	-1	1	37	-18	-1	-24	21	37	2.08	2.46	2.34	2.83	37	7.26	10.24
38	0	0	0	0	38	-7	4	-10	-16	38	1.54	1.77	1.51	2.08	38	3.90	5.50
39	0	0	0	0	39	-11	3	-12	5	39	1.87	2.15	1.93	2.31	39	5.08	7.21
40	-1	0	-1	0	40	-20	-5	-23	-7	40	1.83	2.09	1.95	2.14	40	4.86	7.99
41	0	1	-1	1	41	-13	18	-19	29	41	2.51	3.00	2.78	3.02	41	6.94	9.21
42	-1	0	-1	0	42	-22	-1	-24	2	42	1.70	2.12	1.83	2.25	42	3.87	4.82
43	0	0	0	1	43	-11	14	-13	20	43	2.17	2.50	2.17	2.24	43	3.75	5.44
44	0	0	0	0	44	-7	5	-8	1	44	2.03	2.34	2.02	2.24	44	6.18	8.78
45	0	0	0	0	45	-13	14	-17	1	45	2.03	2.27	2.02	2.14	45	4.07	5.98
46	0	0	0	1	46	1	5	3	34	46	2.87	3.42	2.70	2.68	46	8.49	11.74
47	0	0	-1	0	47	-15	8	-19	5	47	1.79	1.89	1.97	1.94	47	2.66	4.20
48	-1	0	-1	1	48	-21	-1	-26	45	48	2.19	2.42	2.17	2.81	48	5.03	8.08
49	0	1	0	0	49	-5	19	-7	11	49	2.01	2.22	1.98	2.20	49	4.15	7.49
50	0	0	0	1	50	-14	-4	-15	33	50	2.30	2.71	2.35	3.24	50	8.97	12.81
Average	0	0	0	0	Average	-12	5	-14	14	Average	2.17	2.55	2.21	2.61	Average	7.04	10.00

CONS-H-S	F1815/WW/RS																
ME	F1	F2	F3	F4	CFE	F1	F2	F3	F4	MAD	F1	F2	F3	F4	MSE	F1	F2
1	2	-32	1	9	1	55	-1161	44	335	1	10.04	57.71	9.19	13.26	1	63.62	1890.33
2	1	-31	1	9	2	39	-1107	33	326	2	9.85	53.58	10.02	12.70	2	45.73	1619.13
3	2	-32	1	11	3	55	-1139	47	392	3	10.13	58.58	10.17	12.14	3	37.98	1446.92
4	2	-34	2	10	4	79	-1215	78	344	4	10.83	59.67	11.53	13.29	4	65.55	1743.46
5	1	-26	1	7	5	43	-929	40	247	5	8.43	54.78	8.10	10.45	5	45.94	1239.65
6	2	-32	1	10	6	57	-1149	50	353	6	11.18	60.42	10.23	13.09	6	53.47	1956.58
7	1	-30	1	10	7	32	-1088	24	344	7	9.81	53.64	9.82	12.35	7	55.98	1966.54
8	2	-32	2	9	8	73	-1154	71	317	8	11.08	60.45	10.48	12.45	8	40.16	1285.87
9	2	-31	2	9	9	64	-1106	58	326	9	11.41	64.31	11.10	13.78	9	48.53	1629.59
10	2	-31	2	8	10	63	-1129	61	301	10	11.93	64.84	11.53	13.68	10	64.93	2017.45
11	2	-32	2	9	11	69	-1148	65	335	11	8.15	48.09	7.82	10.82	11	34.35	1237.52
12	1	-29	1	10	12	52	-1055	42	352	12	10.98	63.42	10.67	13.03	12	45.23	1466.30
13	1	-29	1	8	13	49	-1050	48	290	13	10.95	61.36	11.07	12.92	13	65.87	1561.53
14	2	-30	2	8	14	62	-1064	61	282	14	11.55	65.46	10.64	12.63	14	43.77	1387.84
15	2	-32	2	9	15	66	-1160	61	332	15	12.49	66.12	12.27	13.35	15	41.47	1647.99
16	2	-32	2	10	16	66	-1165	62	356	16	8.95	54.59	8.85	12.30	16	46.85	1457.47
17	2	-31	2	9	17	60	-1103	57	315	17	10.77	60.55	10.15	11.51	17	56.45	1707.53
18	1	-30	0	9	18	19	-1097	13	320	18	10.69	55.34	10.62	12.56	18	39.22	1531.64
19	2	-28	1	8	19	55	-1013	45	306	19	10.96	61.34	10.40	12.84	19	49.45	1468.68
20	1	-32	1	9	20	54	-1170	47	337	20	8.53	44.11	8.41	11.34	20	42.23	1861.37
21	1	-28	1	8	21	41	-1006	34	285	21	8.85	49.65	9.23	9.68	21	56.80	1802.37
22	2	-31	2	9	22	64	-1099	60	337	22	9.52	52.59	10.10	12.46	22	42.95	1509.45
23	1	-31	1	8	23	43	-1123	38	293	23	10.42	57.56	10.93	12.35	23	68.25	1970.29
24	1	-28	1	9	24	38	-1022	29	311	24	11.10	64.40	10.72	12.48	24	47.82	1281.10
25	2	-32	2	10	25	63	-1137	58	356	25	10.27	60.90	10.16	11.84	25	58.86	1689.78
26	1	-31	1	9	26	38	-1112	35	322	26	10.57	54.55	10.40	11.90	26	62.91	2460.65
27	2	-32	2	10	27	65	-1136	59	343	27	9.59	55.78	9.38	11.49	27	56.64	2073.11
28	2	-29	1	8	28	58	-1044	52	302	28	8.32	47.91	8.84	11.03	28	35.58	918.81
29	2	-31	2	8	29	68	-1104	64	300	29	9.54	51.38	9.61	11.13	29	51.56	1753.55
30	2	-30	1	10	30	60	-1092	51	359	30	10.01	59.30	10.08	13.27	30	54.46	1596.09
31	1	-27	1	8	31	32	-978	21	304	31	8.90	50.53	9.16	10.97	31	33.81	1089.55
32	1	-31	1	10	32	37	-1114	29	367	32	11.18	56.53	11.46	13.96	32	45.10	2112.60
33	2	-30	1	8	33	55	-1086	53	294	33	9.72	54.32	9.72	12.16	33	62.64	2162.38
34	1	-30	1	9	34	49	-1093	48	310	34	10.20	55.80	10.32	11.39	34	58.02	1997.81
35	1	-28	0	7	35	21	-1013	16	264	35	11.62	59.72	11.22	12.73	35	54.73	2124.33
36	1	-32	1	9	36	52	-1153	47	334	36	10.43	56.51	9.90	11.98	36	46.43	1795.22
37	2	-33	2	10	37	59	-1195	56	345	37	9.52	52.34	9.29	13.12	37	31.18	1129.37
38	2	-31	1	9	38	57	-1119	49	325	38	10.64	60.55	10.46	12.97	38	44.90	896.61
39	2	-31	2	9	39	65	-1134	60	315	39	9.83	53.06	10.02	11.76	39	44.13	1755.06
40	2	-33	2	9	40	72	-1195	62	332	40	7.87	42.86	7.95	10.57	40	23.23	1013.00
41	2	-29	2	8	41	62	-1038	61	278	41	8.72	50.54	8.55	11.27	41	47.33	1648.25
42	1	-30	1	9	42	46	-1098	36	308	42	8.17	49.02	8.43	11.65	42	30.24	681.00
43	2	-32	2	11	43	75	-1162	68	395	43	10.54	62.33	10.26	13.62	43	54.52	1707.17
44	2	-29	2	8	44	63	-1056	58	300	44	8.68	49.93	8.48	11.49	44	62.93	2148.78
45	2	-31	2	9	45	60	-1099	55	335	45	10.70	62.74	10.44	12.97	45	48.58	1350.17
46	1	-31	1	9	46	35	-1129	25	333	46	10.09	54.06	10.12	11.24	46	51.28	1753.26
47	1	-29	1	8	47	30	-1058	23	301	47	12.74	65.65	12.84	11.88	47	59.49	2045.08
48	1	-31	1	9	48	36	-1120	32	337	48	10.22	58.45	11.20	13.17	48	67.35	1809.27
49	2	-33	2	9	49	73	-1172	68	332	49	9.14	53.33	9.24	12.60	49	42.43	1270.07
50	1	-31	1	9	50	48	-1115	45	321	50	9.89	57.12	9.80	12.01	50	39.19	1189.69
Average	1	-31	1	9	Average	54	-1099	48	325	Average	10.22	57.17	10.10	12.28	Average	50.05	1636.90

CONS-H-C	MS24665-134																				
ME	F1	F2	F3	F4	CFE	F1	F2	F3	F4	MAD	F1	F2	F3	F4	MSE	F1	F2
1	0	6	-7	7	1	204	-267	258	3828	1	90.44	119.69	85.33	115.24	1	2876.47	7056.73
2	0	8	-3	10	2	297	-109	343	3725	2	86.00	109.96	90.31	112.70	2	3637.45	7763.85
3	0	11	-4	13	3	382	-159	472	4114	3	78.27	109.48	77.34	125.58	3	3445.63	6043.12
4	0	8	-4	10	4	305	-146	348	3945	4	101.97	132.72	98.59	118.70	4	2944.73	7515.09
5	0	14	4	15	5	510	146	556	2932	5	72.91	96.11	73.26	97.50	5	2752.97	5084.05
6	0	17	-7	21	6	601	-253	758	4509	6	78.62	97.16	77.58	128.98	6	2451.90	6453.79
7	0	5	-6	5	7	171	-215	189	3487	7	67.98	94.31	66.08	114.27	7	2632.30	4231.48
8	0	10	-7	14	8	366	-253	489	3748	8	85.37	118.58	84.60	118.78	8	3297.32	4951.46
9	0	10	-3	11	9	345	-123	395	4178	9	96.26	119.61	93.14	129.18	9	2804.63	7988.27
10	0	8	-3	10	10	278	-108	344	3359	10	84.21	110.74	78.76	102.57	10	2330.63	5771.95
11	0	12	-7	14	11	421	-242	500	4254	11	93.30	121.62	99.09	135.13	11	3727.19	7705.66
12	0	0	-13	0	12	-13	-465	0	4220	12	94.70	120.07	96.35	125.11	12	2828.54	6887.98
13	0	13	-1	13	13	478	-20	484	4634	13	86.02	106.76	90.01	147.57	13	2675.06	7187.02
14	0	19	-1	23	14	681	-54	836	4935	14	79.69	96.23	79.59	148.80	14	2874.22	7016.12
15	0	16	-2	19	15	569	-67	694	3508	15	85.28	118.63	81.85	116.14	15	4139.42	7485.47
16	0	9	-4	12	16	332	-157	415	4160	16	83.81	102.38	86.17	131.10	16	3083.47	7099.57
17	0	6	-5	6	17	203	-183	232	4015	17	80.48	109.05	80.07	126.83	17	3778.34	6792.88
18	1	5	-9	7	18	184	-339	248	4606	18	69.11	84.30	71.75	132.57	18	2086.85	3970.34
19	1	7	-7	8	19	255	-242	303	4007	19	113.22	148.27	112.88	124.36	19	3395.25	9050.94
20	1	14	-3	17	20	513	-104	629	4097	20	97.67	125.97	90.96	124.94	20	3208.30	7407.28
21	1	7	-6	8	21	257	-212	278	4100	21	82.22	108.03	83.42	125.22	21	3629.77	7244.59
22	1	12	-10	14	22	441	-345	519	4286	22	70.27	97.61	69.45	143.10	22	3154.74	4797.40
23	1	14	0	15	23	512	-10	554	3316	23	86.81	119.64	85.49	116.78	23	4179.81	8284.14
24	1	11	-8	13	24	387	-303	478	4223	24	77.65	99.42	81.81	122.48	24	2659.85	5418.77
25	1	2	-16	5	25	81	-568	191	3152	25	87.11	111.46	81.00	109.21	25	3128.71	8192.95
26	1	7	5	7	26	238	179	236	3244	26	85.07	105.88	79.39	112.86	26	3158.25	8780.24
27	1	4	-10	5	27	130	-354	196	4482	27	84.54	113.00	82.21	137.47	27	2794.82	5443.33
28	1	15	3	17	28	549	102	615	3976	28	88.02	114.97	89.89	123.10	28	2969.07	5997.44
29	1	5	-12	7	29	176	-423	257	4692	29	75.99	100.85	75.90	143.83	29	3217.65	5860.56
30	1	14	-2	16	30	505	-72	584	5039	30	78.85	107.41	78.82	146.77	30	2855.96	4991.04
31	1	9	-6	9	31	309	-233	339	4294	31	82.79	103.55	86.30	130.94	31	3482.37	7129.27
32	1	0	-11	2	32	13	-406	87	3548	32	83.95	108.00	84.11	119.09	32	2669.81	6191.85
33	1	8	-16	12	33	271	-594	439	4020	33	93.71	124.42	89.02	127.14	33	3413.97	6930.63
34	1	10	-3	13	34	353	-118	472	3453	34	92.37	119.80	92.28	115.23	34	2759.82	6181.95
35	1	3	-2	4	35	119	-82	138	3918	35	80.35	106.66	71.07	111.37	35	2712.39	6238.42
36	1	0	-6	0	36	15	-205	11	3024	36	94.35	115.55	98.97	102.19	36	3434.22	9087.12
37	1	13	1	15	37	480	47	522	4855	37	76.64	103.69	68.12	137.98	37	2617.89	6406.39
38	1	5	-10	7	38	195	-364	246	4907	38	73.56	105.22	75.29	139.79	38	3403.57	4793.04
39	1	11	-2	14	39	402	-82	508	3850	39	74.67	101.98	80.39	112.54	39	3111.70	5339.20
40	1	11	-9	12	40	388	-323	443	4660	40	76.72	103.87	71.59	134.31	40	2290.63	4472.12
41	1	9	-8	11	41	330	-278	396	3609	41	96.26	126.25	86.52	112.99	41	2891.54	7165.22
42	1	7	-7	10	42	259	-239	363	3356	42	74.59	100.53	82.02	113.17	42	3514.11	5462.37
43	1	6	-2	6	43	213	-86	212	3995	43	74.81	102.69	73.81	131.10	43	3331.65	5893.86
44	1	12	-2	14	44	439	-57	513	4196	44	95.42	120.50	89.02	132.84	44	2862.29	7543.03
45	1	-1	-4	-1	45	-38	-137	-24	3761	45	99.98	130.12	98.32	129.33	45	2607.20	6168.95
46	1	10	-6	14	46	371	-207	507	4069	46	94.83	124.50	99.28	121.84	46	3177.03	6397.22
47	1	12	-5	15	47	445	-195	556	3406	47	80.28	105.98	75.78	112.53	47	2855.39	6156.38
48	1	12	-1	13	48	419	-39	485	3777	48	79.77	94.18	84.88	111.84	48	2263.45	5766.91
49	1	12	-4	13	49	429	-149	473	2647	49	82.64	113.39	80.26	91.72	49	3680.25	6571.14
50	1	4	-10	7	50	158	-352	237	4541	50	87.56	117.85	82.63	134.36	50	4028.28	8081.14
Average	0	9	-5	11	Average	334	-188	401	4019	Average	84.64	110.36	84.11	125.22	Average	3089.73	6618.58

REP-H-C	ZP650-SC-M-B-3																	
ME	F1	F2	F3	F4	CFE	F1	F2	F3	F4	MAD	F1	F2	F3	F4	MSE	F1	F2
1	1	-8	0	1	1	29	-279	5	30	1	6.28	8.36	6.88	8.92	1	16.49	51.18
2	1	-8	0	1	2	24	-281	6	33	2	6.26	8.62	6.83	8.37	2	18.51	56.15
3	0	-7	0	1	3	11	-262	0	26	3	5.93	8.21	6.76	8.24	3	15.14	45.55
4	1	-7	0	1	4	22	-261	4	23	4	6.18	7.99	6.77	8.48	4	14.39	46.79
5	1	-8	0	1	5	29	-287	3	36	5	6.57	8.45	7.25	9.23	5	11.48	44.26
6	1	-8	0	1	6	23	-282	5	34	6	6.75	8.38	7.21	9.36	6	16.24	52.71
7	1	-8	0	1	7	24	-279	7	31	7	6.42	8.39	7.05	8.86	7	17.44	54.44
8	1	-7	0	1	8	21	-268	0	27	8	5.70	8.16	6.32	7.49	8	15.89	48.27
9	1	-8	0	1	9	19	-278	4	33	9	5.93	8.11	6.39	8.38	9	15.08	45.19
10	1	-7	0	1	10	21	-259	6	22	10	6.54	7.68	7.00	9.33	10	17.26	49.90
11	0	-7	0	1	11	13	-250	4	18	11	5.55	7.33	6.19	7.50	11	12.70	40.28
12	1	-7	0	1	12	24	-269	5	26	12	5.83	7.95	6.46	8.25	12	15.62	46.32
13	1	-8	0	1	13	26	-272	4	27	13	5.41	7.91	5.86	7.81	13	14.82	41.51
14	0	-7	0	1	14	15	-257	4	23	14	6.05	7.67	6.76	8.73	14	15.23	42.17
15	1	-7	0	1	15	20	-267	2	26	15	5.91	7.87	6.44	8.53	15	15.17	42.60
16	1	-8	0	1	16	29	-279	5	30	16	6.28	8.38	6.88	8.92	16	16.49	51.18
17	1	-8	0	1	17	26	-280	5	32	17	6.60	8.44	7.03	9.06	17	16.84	53.38
18	1	-8	0	1	18	22	-278	5	31	18	5.92	8.00	6.34	8.35	18	14.70	43.00
19	1	-7	0	1	19	21	-268	0	27	19	6.36	7.89	7.13	9.46	19	17.02	47.10
20	1	-8	0	1	20	22	-272	7	28	20	5.83	8.07	6.34	8.67	20	17.35	44.08
21	0	-7	0	1	21	17	-267	4	27	21	5.82	7.93	6.32	8.18	21	15.47	41.89
22	1	-7	0	1	22	19	-252	4	20	22	6.23	7.86	6.75	8.11	22	10.02	39.72
23	0	-7	0	1	23	16	-262	1	25	23	5.65	7.85	6.19	8.06	23	12.98	40.17
24	1	-8	0	1	24	18	-277	-1	33	24	6.10	8.41	7.03	8.47	24	14.86	47.62
25	0	-7	0	1	25	18	-265	3	26	25	6.14	7.91	6.57	8.95	25	15.76	45.27
26	1	-8	0	1	26	26	-278	4	31	26	5.55	8.10	6.26	8.53	26	18.54	45.17
27	0	-7	0	1	27	11	-259	-4	25	27	5.39	7.58	5.88	7.86	27	15.65	40.12
28	1	-7	0	1	28	20	-266	5	26	28	6.01	8.12	6.65	8.11	28	17.62	47.31
29	0	-8	0	1	29	15	-275	-1	33	29	5.81	8.00	6.63	7.98	29	17.11	51.74
30	1	-7	0	1	30	20	-262	3	25	30	5.76	7.73	6.32	8.06	30	13.87	42.52
31	1	-8	0	1	31	19	-272	1	30	31	6.34	8.04	7.01	8.85	31	14.70	48.26
32	1	-7	0	1	32	21	-253	2	20	32	5.63	7.46	6.03	7.82	32	10.52	38.33
33	0	-7	0	1	33	13	-253	0	22	33	5.74	7.50	6.34	8.06	33	12.63	38.36
34	0	-7	0	1	34	18	-270	3	30	34	5.87	8.09	6.37	7.85	34	13.30	42.44
35	1	-8	0	1	35	21	-282	-1	35	35	6.02	8.30	6.82	8.40	35	15.10	43.69
36	1	-7	0	1	36	28	-269	4	27	36	5.35	8.00	6.04	7.68	36	14.33	37.59
37	1	-7	0	1	37	21	-268	4	28	37	5.90	7.85	6.48	8.60	37	17.85	48.09
38	0	-7	0	1	38	17	-267	3	27	38	5.81	7.98	6.29	8.17	38	16.91	43.70
39	1	-7	0	1	39	19	-262	2	25	39	5.75	7.72	6.26	7.75	39	10.09	41.51
40	0	-7	0	1	40	17	-253	0	20	40	5.61	7.32	6.22	8.20	40	12.98	39.25
41	1	-7	0	1	41	18	-257	4	22	41	6.06	7.60	6.62	8.46	41	9.51	39.46
42	0	-7	0	1	42	12	-259	4	25	42	5.96	7.78	6.55	8.22	42	13.75	44.27
43	1	-7	0	1	43	18	-260	4	24	43	5.86	7.73	6.43	8.24	43	12.73	38.65
44	1	-8	0	1	44	21	-275	3	30	44	5.95	8.17	6.40	8.19	44	12.50	42.97
45	1	-7	0	1	45	22	-259	4	23	45	5.96	7.64	6.63	8.42	45	14.80	45.24
46	0	-8	0	1	46	18	-284	0	37	46	5.58	8.25	6.25	7.92	46	13.33	43.99
47	0	-7	0	1	47	5	-263	-5	29	47	5.60	7.95	6.22	7.63	47	13.54	41.80
48	1	-8	0	1	48	21	-271	-2	29	48	5.96	7.83	6.42	8.39	48	14.73	49.01
49	1	-8	0	1	49	28	-273	4	28	49	6.14	7.88	6.76	9.07	49	14.05	41.85
50	0	-7	0	1	50	16	-255	2	21	50	6.37	8.19	6.99	8.88	50	17.38	50.97
Average	1	-7	0	1	Average	21	-269	3	28	Average	6.02	8.03	6.61	8.47	Average	15.34	46.07

REPH-S	2-1517																
ME	F1	F2	F3	F4	CFE	F1	F2	F3	F4	MAD	F1	F2	F3	F4	MSE	F1	F2
1	0	0	0	3	1	2	-3	9	107	1	6.85	6.53	5.69	5.25	1	13.44	12.03
2	0	0	0	3	2	2	-4	7	106	2	6.73	6.40	5.73	5.22	2	13.62	13.02
3	0	0	0	3	3	2	-2	7	90	3	6.30	5.99	5.29	4.97	3	11.00	10.24
4	0	0	0	3	4	2	-2	6	93	4	6.30	6.05	5.46	4.97	4	13.35	12.53
5	0	0	0	3	5	1	-4	6	94	5	6.61	6.28	5.66	5.19	5	14.73	13.19
6	0	0	0	3	6	2	-4	8	98	6	6.28	6.06	5.55	4.95	6	12.05	11.02
7	0	0	0	3	7	1	-3	6	101	7	6.38	6.02	5.33	4.85	7	10.90	10.23
8	0	0	0	3	8	2	-3	8	105	8	6.80	6.49	5.80	5.30	8	13.17	11.81
9	0	0	0	3	9	2	-3	6	100	9	6.61	6.28	5.47	5.12	9	10.80	9.95
10	0	0	0	2	10	1	-4	3	89	10	6.42	6.09	5.37	4.93	10	10.77	9.82
11	0	0	0	3	11	2	-3	10	103	11	6.59	6.28	5.55	5.10	11	13.47	12.47
12	0	0	0	3	12	2	-3	8	102	12	6.57	6.24	5.61	5.10	12	12.97	12.32
13	0	0	0	3	13	1	-4	5	102	13	6.67	6.35	5.73	5.19	13	13.83	12.60
14	0	0	0	3	14	2	-4	7	102	14	6.98	6.60	5.68	5.38	14	13.08	11.49
15	0	0	0	3	15	0	-7	4	98	15	6.36	6.03	5.29	4.88	15	11.86	10.48
16	0	0	0	3	16	1	-2	6	105	16	6.74	6.42	5.70	5.17	16	12.87	11.38
17	0	0	0	3	17	3	-2	10	96	17	6.53	6.26	5.54	5.05	17	13.83	11.87
18	0	0	0	3	18	1	-6	3	99	18	6.36	6.11	5.52	4.98	18	12.65	11.19
19	0	0	0	3	19	1	-5	4	106	19	6.76	6.41	5.56	5.21	19	10.61	9.40
20	0	0	0	3	20	1	-4	7	97	20	6.68	6.38	5.69	5.20	20	12.21	10.80
21	0	0	0	3	21	1	-4	5	92	21	6.50	6.18	5.48	5.07	21	11.35	10.33
22	0	0	0	3	22	1	-4	3	99	22	6.55	6.24	5.52	5.12	22	11.31	10.52
23	0	0	0	3	23	2	-4	7	95	23	6.24	6.00	5.33	4.91	23	12.08	10.59
24	0	0	0	3	24	1	-4	6	101	24	6.90	6.56	5.74	5.40	24	12.74	11.15
25	0	0	0	3	25	1	-4	4	103	25	6.69	6.36	5.65	5.13	25	11.83	10.87
26	0	0	0	3	26	2	-4	9	98	26	6.47	6.12	5.41	4.97	26	13.82	12.84
27	0	0	0	3	27	1	-3	5	102	27	6.51	6.17	5.51	4.99	27	12.34	11.48
28	0	0	0	3	28	1	-4	7	103	28	6.51	6.28	5.77	5.12	28	13.57	12.08
29	0	0	0	3	29	1	-5	6	102	29	6.54	6.29	5.67	5.20	29	13.53	12.82
30	0	0	0	3	30	3	-2	9	99	30	6.40	6.03	5.24	4.88	30	11.48	10.78
31	0	0	0	3	31	2	-2	6	92	31	6.52	6.19	5.36	4.95	31	10.17	8.57
32	0	0	0	3	32	1	-6	8	102	32	6.53	6.25	5.63	5.10	32	13.81	11.99
33	0	0	0	3	33	0	-5	3	92	33	6.62	6.39	5.71	5.27	33	13.24	11.29
34	0	0	0	3	34	1	-2	5	91	34	6.36	6.05	5.48	4.88	34	13.12	12.21
35	0	0	0	2	35	1	-2	5	89	35	6.63	6.32	5.59	5.22	35	12.52	11.12
36	0	0	0	3	36	2	-2	7	100	36	6.45	6.20	5.56	4.94	36	13.25	11.77
37	0	0	0	3	37	2	-3	7	99	37	6.42	6.10	5.43	5.00	37	13.32	12.06
38	0	0	0	3	38	3	-2	10	100	38	6.54	6.20	5.34	4.95	38	11.64	10.61
39	0	0	0	3	39	2	-4	9	98	39	6.44	6.08	5.30	4.94	39	11.13	10.12
40	0	0	0	3	40	1	-3	4	96	40	6.62	6.37	5.60	5.11	40	12.83	10.59
41	0	0	0	3	41	1	-6	7	110	41	6.64	6.32	5.52	5.09	41	13.18	11.57
42	0	0	0	3	42	1	-5	6	99	42	6.72	6.50	5.86	5.23	42	15.41	12.74
43	0	0	0	3	43	0	-5	1	90	43	6.32	6.07	5.45	4.93	43	11.03	9.78
44	0	0	0	3	44	2	-2	6	102	44	6.65	6.38	5.70	5.17	44	14.59	12.56
45	0	0	0	3	45	2	-2	9	97	45	6.50	6.14	5.44	5.00	45	14.48	13.18
46	0	0	0	3	46	2	0	4	92	46	6.48	6.16	5.48	5.01	46	11.25	10.12
47	0	0	0	3	47	1	-4	8	101	47	6.66	6.36	5.71	5.23	47	11.39	10.50
48	0	0	0	3	48	2	-3	10	100	48	6.62	6.31	5.44	5.01	48	12.21	10.30
49	0	0	0	3	49	1	-3	7	99	49	6.68	6.34	5.60	5.16	49	13.46	11.85
50	0	0	0	3	50	1	-4	8	96	50	6.39	6.10	5.52	5.05	50	11.77	10.79
Average	0	0	0	3	Average	1	-4	6	99	Average	6.56	6.25	5.55	5.09	Average	12.48	11.30

REP-L-C	622-2362-001																	
ME	F1	F2	F3	F4	CFE	F1	F2	F3	F4	MAD	F1	F2	F3	F4	MSE	F1	F2	
1	0	0	0	1	1	1	0	0	51	1	3.67	6.62	3.90	3.39	1	4.90	20.63	
2	0	0	0	1	2	-1	2	-2	52	2	3.71	6.66	4.01	3.43	2	4.93	21.59	
3	0	0	0	2	3	-2	2	-3	54	3	3.98	7.29	4.27	3.62	3	6.06	24.99	
4	0	0	0	1	4	-1	2	-2	45	4	3.65	6.47	3.91	3.25	4	4.44	20.97	
5	0	0	0	1	5	0	1	-1	51	5	3.65	6.64	3.90	3.46	5	5.20	22.68	
6	0	0	0	1	6	-3	2	-3	51	6	3.82	6.68	4.12	3.42	6	4.73	22.63	
7	0	0	0	1	7	2	-1	0	54	7	3.94	7.04	4.28	3.58	7	6.33	26.87	
8	0	0	0	1	8	-2	2	-3	49	8	3.70	6.61	3.99	3.40	8	4.91	22.03	
9	0	0	0	1	9	-1	1	-2	52	9	3.85	6.87	4.14	3.54	9	5.23	24.38	
10	0	0	0	2	10	1	0	0	54	10	3.81	7.00	4.09	3.61	10	6.04	24.79	
11	0	0	0	2	11	0	2	-2	60	11	3.94	7.17	4.21	3.73	11	6.10	25.90	
12	0	0	0	1	12	-3	3	-4	51	12	3.99	7.11	4.34	3.51	12	5.76	26.27	
13	0	0	0	1	13	-6	4	-5	52	13	3.87	6.87	4.13	3.49	13	4.88	23.75	
14	0	0	0	2	14	-1	2	-3	55	14	3.76	6.92	3.97	3.58	14	5.34	22.42	
15	0	0	0	2	15	2	0	0	56	15	4.01	7.20	4.28	3.71	15	6.37	27.37	
16	0	0	0	1	16	-3	3	-4	48	16	3.63	6.54	3.91	3.30	16	4.62	20.29	
17	0	0	0	1	17	-3	2	-3	48	17	3.66	6.57	3.96	3.40	17	5.19	23.08	
18	0	0	0	1	18	-3	2	-3	48	18	3.84	6.77	4.17	3.32	18	5.09	22.84	
19	0	0	0	2	19	0	1	-2	60	19	4.11	7.28	4.39	3.82	19	5.98	28.07	
20	0	0	0	1	20	5	-3	3	51	20	3.72	6.85	4.01	3.45	20	6.62	25.05	
21	0	0	0	1	21	-2	3	-4	53	21	3.85	6.80	4.15	3.56	21	5.17	24.97	
22	0	0	0	2	22	0	0	-1	55	22	3.97	7.08	4.24	3.61	22	5.55	25.32	
23	0	0	0	2	23	0	1	-1	57	23	4.00	7.21	4.33	3.62	23	6.03	24.71	
24	0	0	0	1	24	0	1	-2	51	24	3.84	6.90	4.16	3.43	24	5.78	23.67	
25	0	0	0	1	25	-2	2	-3	51	25	3.76	6.78	4.03	3.44	25	4.92	22.50	
26	0	0	0	1	26	-3	2	-3	49	26	3.89	6.77	4.20	3.50	26	5.33	26.50	
27	0	0	0	1	27	3	-2	2	50	27	3.86	6.87	4.16	3.49	27	6.31	25.96	
28	0	0	0	2	28	0	2	-3	57	28	3.83	7.01	4.11	3.62	28	5.47	23.09	
29	0	0	0	1	29	-2	2	-2	53	29	3.71	6.83	3.93	3.52	29	5.53	22.61	
30	0	0	0	2	30	-2	3	-3	56	30	3.85	6.81	4.13	3.59	30	5.07	24.20	
31	0	0	0	1	31	-1	2	-2	54	31	3.69	6.84	3.99	3.46	31	6.10	23.38	
32	0	0	0	2	32	0	1	-1	55	32	3.96	7.09	4.24	3.64	32	5.67	25.89	
33	0	0	0	1	33	-6	4	-6	42	33	3.63	6.46	3.95	3.19	33	4.79	21.76	
34	0	0	0	1	34	1	0	0	48	34	3.83	6.76	4.14	3.42	34	5.73	25.16	
35	0	0	0	1	35	-1	1	-2	49	35	3.64	6.45	3.90	3.35	35	4.77	22.73	
36	0	0	0	1	36	-3	3	-3	52	36	3.97	7.16	4.32	3.49	36	6.15	26.44	
37	0	0	0	1	37	-4	3	-4	52	37	4.15	7.28	4.49	3.57	37	6.07	27.12	
38	0	0	0	2	38	2	0	0	57	38	3.83	6.84	4.10	3.55	38	5.43	23.77	
39	0	0	0	1	39	-1	1	-1	45	39	3.76	6.63	4.07	3.33	39	5.38	24.39	
40	0	0	0	1	40	-2	1	-1	49	40	3.95	6.82	4.28	3.47	40	5.11	24.59	
41	0	0	0	1	41	-1	1	-2	54	41	3.88	6.81	4.15	3.59	41	5.57	26.73	
42	0	0	0	2	42	3	0	1	57	42	4.13	7.33	4.47	3.74	42	6.80	29.04	
43	0	0	0	1	43	-1	0	-1	50	43	4.00	7.13	4.35	3.53	43	6.42	27.63	
44	0	0	0	1	44	-2	3	-4	51	44	3.76	6.77	4.06	3.42	44	5.14	22.50	
45	0	0	0	1	45	-10	6	-6	45	45	3.70	6.58	4.04	3.25	45	4.83	21.52	
46	0	0	0	1	46	1	0	-1	47	46	3.81	6.50	3.85	3.35	46	4.73	20.80	
47	0	0	0	1	47	-2	2	-3	50	47	3.90	6.87	4.23	3.42	47	5.62	24.92	
48	0	0	0	1	48	3	0	0	53	48	3.84	6.77	4.14	3.56	48	5.48	25.60	
49	0	0	0	1	49	1	1	-1	47	49	3.73	6.48	4.02	3.32	49	4.42	20.86	
50	0	0	0	1	50	-1	0	-1	50	50	3.78	6.72	4.02	3.48	50	5.38	24.30	
Average	0	0	0	1	Average	-1	1	-2	53	Average	3.83	6.88	4.11	3.51	Average	5.49	24.04	

REP-L-S	DH1030-24-600CS																
ME	F1	F2	F3	F4	CFE	F1	F2	F3	F4	MAD	F1	F2	F3	F4	MSE	F1	F2
1	0	-4	0	3	1	3	-132	2	117	1	4.60	4.06	4.67	3.94	1	9.11	12.73
2	0	-4	0	4	2	4	-153	6	136	2	4.93	4.60	4.76	4.42	2	7.26	12.62
3	0	-4	0	3	3	0	-134	0	118	3	4.85	4.09	4.74	3.93	3	8.24	12.16
4	0	-4	0	3	4	2	-138	4	117	4	4.46	4.10	4.37	3.85	4	7.14	11.92
5	0	-4	0	3	5	2	-138	2	122	5	4.94	4.33	4.90	4.02	5	9.17	14.46
6	0	-4	0	3	6	1	-136	2	118	6	5.25	4.28	5.14	4.03	6	12.04	15.22
7	0	-4	0	4	7	6	-160	9	144	7	5.41	4.97	5.32	4.69	7	8.98	15.98
8	0	-4	0	3	8	1	-132	2	114	8	4.45	4.07	4.49	3.83	8	8.22	11.98
9	0	-4	0	4	9	4	-143	6	127	9	5.07	4.42	5.07	4.20	9	11.26	15.56
10	0	-4	0	3	10	1	-134	2	116	10	4.81	4.10	4.67	3.91	10	8.42	11.53
11	0	-4	0	4	11	2	-158	4	138	11	5.37	4.76	5.33	4.48	11	9.73	15.58
12	0	-4	0	3	12	2	-138	3	121	12	4.76	4.18	4.65	4.07	12	7.68	12.07
13	0	-4	0	3	13	6	-136	8	119	13	4.63	4.15	4.52	3.99	13	8.60	12.19
14	0	-4	0	3	14	-1	-139	-2	123	14	5.14	4.42	5.07	4.16	14	8.64	13.30
15	0	-4	0	3	15	-1	-133	0	112	15	4.59	3.97	4.55	3.77	15	7.06	11.40
16	0	-4	0	3	16	1	-137	2	121	16	4.68	4.15	4.48	3.90	16	8.73	12.23
17	0	-4	0	3	17	4	-133	5	114	17	4.53	3.92	4.32	3.80	17	6.93	11.27
18	0	-4	0	3	18	1	-140	3	121	18	4.89	4.16	4.64	4.01	18	5.97	10.58
19	0	-4	0	3	19	1	-131	2	113	19	4.58	4.08	4.49	3.83	19	7.29	11.63
20	0	-4	0	3	20	-2	-131	-3	113	20	4.81	4.10	4.70	3.87	20	7.37	11.19
21	0	-4	0	3	21	2	-126	2	110	21	4.61	3.89	4.57	3.81	21	7.69	11.35
22	0	-4	0	4	22	2	-144	4	127	22	5.03	4.39	4.94	4.18	22	8.70	14.12
23	0	-4	0	4	23	4	-149	6	129	23	5.36	4.54	5.21	4.25	23	10.51	15.24
24	0	-4	0	4	24	1	-145	2	126	24	5.02	4.42	5.03	4.16	24	8.09	13.26
25	0	-4	0	3	25	2	-134	3	118	25	4.95	4.26	4.90	4.02	25	10.52	14.28
26	0	-4	0	3	26	2	-133	3	115	26	4.79	4.11	4.79	3.92	26	7.68	12.17
27	0	-4	0	3	27	3	-131	4	112	27	4.85	4.10	4.77	3.87	27	8.33	12.48
28	0	-4	0	4	28	5	-148	7	132	28	5.04	4.55	4.95	4.38	28	6.98	13.08
29	0	-4	0	4	29	4	-145	5	130	29	5.44	4.69	5.52	4.37	29	11.20	16.59
30	0	-4	0	3	30	3	-130	4	113	30	4.75	4.08	4.66	3.82	30	9.27	12.32
31	0	-4	0	3	31	6	-143	8	125	31	5.19	4.51	5.11	4.17	31	9.61	15.12
32	0	-4	0	3	32	4	-128	5	111	32	4.48	3.85	4.26	3.69	32	7.10	11.09
33	0	-4	0	3	33	5	-138	6	121	33	4.87	4.26	4.74	4.01	33	9.28	13.90
34	0	-4	0	4	34	0	-155	0	140	34	5.28	4.69	5.18	4.47	34	10.12	14.94
35	0	-4	0	4	35	5	-147	8	127	35	5.10	4.58	5.07	4.30	35	8.45	14.63
36	0	-4	0	3	36	3	-135	3	119	36	4.77	4.08	4.54	3.97	36	8.52	12.36
37	0	-4	0	3	37	2	-138	4	118	37	4.78	4.24	4.74	3.96	37	7.08	12.25
38	0	-4	0	3	38	2	-138	3	121	38	4.81	4.16	4.72	4.01	38	7.26	12.21
39	0	-4	0	3	39	3	-141	5	122	39	5.07	4.35	5.12	4.11	39	9.71	14.72
40	0	-4	0	3	40	5	-131	8	110	40	4.69	4.06	4.62	3.78	40	9.87	13.66
41	0	-4	0	3	41	2	-139	3	122	41	4.88	4.19	4.62	4.07	41	6.94	11.72
42	0	-4	0	3	42	-1	-139	-1	123	42	4.83	4.22	4.68	4.04	42	7.48	11.56
43	0	-4	0	4	43	4	-147	6	131	43	4.95	4.56	4.93	4.28	43	9.74	14.88
44	0	-4	0	4	44	3	-144	5	127	44	5.25	4.44	5.10	4.25	44	9.75	13.97
45	0	-4	0	4	45	4	-150	6	133	45	4.95	4.42	4.74	4.29	45	6.48	12.96
46	0	-4	0	3	46	3	-128	5	109	46	4.75	4.09	4.74	3.82	46	8.78	13.63
47	0	-4	0	3	47	0	-126	-1	110	47	4.56	3.92	4.56	3.67	47	6.57	10.14
48	0	-4	0	3	48	3	-136	4	117	48	4.88	4.35	4.97	3.98	48	8.71	13.79
49	0	-4	0	3	49	3	-141	4	123	49	4.89	4.38	4.91	4.10	49	11.37	14.69
50	0	-4	0	4	50	5	-152	7	134	50	5.33	4.50	5.17	4.41	50	8.50	15.14
Average	0	-4	0	3	Average	2	-138	3	121	Average	4.88	4.26	4.80	4.04	Average	8.55	13.02

Appendix K: Final Non-Parametric Test on Simulated Demand

NON-PARAMETRIC TEST		FRIEDMAN TEST	
Ho:All Forecasting Techniques are equal			
b=	150	$[R(X_{ij})]^2$	4500
k=	4	ΣR_j^2	582594
K_1=	3	A_2=	4500
K_2=	447	B_2=	3884
T_2=	32 (T statitstics)		
Overall p-value=	0.010		
F (α, K_1, K_2)	3.826 (critical value)		
Reject H_o ?	Yes (T_2>F)		

Consumable
Low Demand
Common

α	$t_{1-0.99/2,1119}$	$T_{critical}$
0.99	2.58688	52.600

$R > T_{critical}$; next level

Note: Adapted from Conover, J. 1980: 300

$$| R_{fn-1} - R_f | > t_{1-\alpha/2}\left[\frac{2b(A_2 - B_2)}{(b-1)(k-1)}\right]^{\frac{1}{2}}$$

MULTIPLE COMPARISON

Treat	Rank	I	II	III
F1	278	A		
F3	339		B	
F4	425			C
F2	458			C

Note: This test include the results obtained in ME, MAD, and MSE for each individual of the 50 replication.

NON-PARAMETRIC TEST		FRIEDMAN TEST	
Ho:All Forecasting Techniques are equal			
b=	150	$[R(X_{ij})]^2$	4500
k=	4	ΣR_j^2	664022
K_1=	3	A_2=	4500
K_2=	447	B_2=	4427
T_2=	1378 (T statitstics)		
Overall p-value=	0.010		
F (α, K_1, K_2)	3.826 (critical value)		
Reject H_o ?	Yes (T_2>F)		

Consumable
High Demand
Specific

α	$t_{1-0.99/2,1119}$	$T_{critical}$
0.99	2.58688	18.130

$R > T_{critical}$; next level

Note: Adapted from Conover, J. 1980: 300

$$| R_{fn-1} - R_f | > t_{1-\alpha/2}\left[\frac{2b(A_2 - B_2)}{(b-1)(k-1)}\right]^{\frac{1}{2}}$$

MULTIPLE COMPARISON

Treat	Rank	I	II	III	IV
F3	195	A			
F1	259		B		
F4	446			C	
F2	600				D

Note: This test include the results obtained in ME, MAD, and MSE for each individual of the 50 replication.

NON-PARAMETRIC TEST		FRIEDMAN TEST	
Ho:All Forecasting Techniques are equal			
b=	150	$[R(X_{ij})]^2$	4500
k=	4	ΣRj^2	637704
K_1=	3	A_2=	4500
K_2=	447	B_2=	4251
T_2=	300 (T statitstics)		
Overall p-value=	**0.010**		
F (α, K_1, K_2)	**3.826** (critical value)		
Reject H_o ?	**Yes** (T_2>F)		

Consumable
High Demand
Common

α	$t_{1-0.99/2,1119}$	$T_{critical}$
0.99	2.58688	**33.417**

$R > T_{critical}$; next level

Note: Adapted from Conover, J. 1980: 300

$$| R_{fn-1} - R_f | > t_{1-\alpha/2}\left[\frac{2b(A_2 - B_2)}{(b-1)(k-1)}\right]^{\frac{1}{2}}$$

MULTIPLE COMPARISON

Treat	Rank	I	II	III
F1	228	A		
F3	254	A		
F4	548		B	
F2	470			C

Note: This test include the results obtained in ME, MAD, and MSE for each individual of the 50 replication.

NON-PARAMETRIC TEST		FRIEDMAN TEST	
Ho:All Forecasting Techniques are equal			
b=	150	$[R(X_{ij})]^2$	4500
k=	4	ΣRj^2	653702
K_1=	3	A_2=	4500
K_2=	447	B_2=	4358
T_2=	638 (T statitstics)		
Overall p-value=	**0.010**		
F (α, K_1, K_2)	**3.826** (critical value)		
Reject H_o ?	**Yes** (T_2>F)		

Repairable
High Demand
Common

α	$t_{1-0.99/2,1119}$	$T_{critical}$
0.99	2.58688	**25.253**

$R > T_{critical}$; next level

Note: Adapted from Conover, J. 1980: 300

$$| R_{fn-1} - R_f | > t_{1-\alpha/2}\left[\frac{2b(A_2 - B_2)}{(b-1)(k-1)}\right]^{\frac{1}{2}}$$

MULTIPLE COMPARISON

Treat	Rank	I	II	III	IV
F1	209	A			
F3	244		B		
F4	489			C	
F2	558				D

Note: This test include the results obtained in ME, MAD, and MSE for each individual of the 50 replication.

NON-PARAMETRIC TEST			FRIEDMAN TEST
Ho:All Forecasting Techniques are equal			

Repairable
High Demand
Specific

b=	150	$[R(Xij)]^2$	4500
k=	4	ΣRj^2	574682
K_1=	3	A_2=	4500
K_2=	447	B_2=	3831
T_2=	18 (T statitstics)		
Overall p-value=	0.010		
$F(\alpha, K_1, K_2)$	3.826 (critical value)		
Reject H_o ?	Yes (T_2>F)		

α	$t_{1-0.99/2,1119}$	$T_{critical}$
0.99	2.58688	54.806

R> $T_{critical}$; next level

Note: Adapted from Conover, J. 1980: 300

$$|R_{fn-1} - R_f| > t_{1-\alpha/2}\left[\frac{2b(A_2 - B_2)}{(b-1)(k-1)}\right]^{\frac{1}{2}}$$

MULTIPLE COMPARISON

Treat	Rank	I	II	III
F3	314	A		
F2	331	A	B	
F1	405		B	C
F4	450			C

Note: This test include the results obtained in CFE, MAD, and MSE for each individual of the 50 replication.

NON-PARAMETRIC TEST			FRIEDMAN TEST
Ho:All Forecasting Techniques are equal			

Repairable
Low Demand
Common

b=	150	$[R(Xij)]^2$	4500
k=	4	ΣRj^2	588614
K_1=	3	A_2=	4500
K_2=	447	B_2=	3924
T_2=	45 (T statitstics)		
Overall p-value=	0.010		
$F(\alpha, K_1, K_2)$	3.826 (critical value)		
Reject H_o ?	Yes (T_2>F)		

α	$t_{1-0.99/2,1119}$	$T_{critical}$
0.99	2.58688	50.858

R> $T_{critical}$; next level

Note: Adapted from Conover, J. 1980: 300

$$|R_{fn-1} - R_f| > t_{1-\alpha/2}\left[\frac{2b(A_2 - B_2)}{(b-1)(k-1)}\right]^{\frac{1}{2}}$$

MULTIPLE COMPARISON

Treat	Rank	I	II	III
F1	249	A		
F3	378		B	
F4	400		B	
F2	473			C

Note: This test include the results obtained in ME, MAD, and MSE for each individual of the 50 replication.

NON-PARAMETRIC TEST				FRIEDMAN TEST
Ho:All Forecasting Techniques are equal				
b=	150	$[R(Xij)]^2$	4500	Repairable Low Demand Specific
k=	4	ΣRj^2	574200	
K_1=	3	A_2=	4500	
K_2=	447	B_2=	3828	
T_2=	17 (T statitstics)			
Overall p-value=	**0.010**			
F (α, K_1, K_2)	**3.826** (critical value)			
Reject H_o ?	**Yes** (T_2>F)			

α	$t_{1-0.99/2,1119}$	$T_{critical}$
0.99	2.58688	**54.937**

R> $T_{critical}$; next level

Note: Adapted from Conover, J. 1980: 300

$$|R_{fn-1} - R_f| > t_{1-\alpha/2}\left[\frac{2b(A_2 - B_2)}{(b-1)(k-1)}\right]^{\frac{1}{2}}$$

MULTIPLE COMPARISON

Treat	Rank	I	II
F1	310	A	
F3	340	A	
F4	400		B
F2	450		B

Note: This test include the results obtained in ME, MAD, and MSE for each individual of the 50 replication.

Appendix L: Cost Comparison Current System versus the Forecasting System

Single Exponential	Part Category	Part Number	Unit Cost	Starting Inventory (SI)	$Prob_{Stockout}$ Proposal	$Prob_{Stockout}$ Current (Rc)	Total Cost (CP_{NPV})	Carrying cost [r]	Inflation (i)	Reject Ho:
	CONS-L-C	307	$1.23	70	0.0%	0.0%	$132.08	0.3	0.04	Yes

No. Period n	Month	Actual Value Xi	Forecast Value Fi	Replenish Proposal Rp	Ending Inventory Ep=SI-Xi+Rp	Replenish Current Rc	Ending Inventory Ec=SI-Xi+Rc	Purchase Cost CP($)	Differences D Ec-Ep	Cost of Difference D_{NPV}($)
1	Jan	0	9		70		70	0.00	0	0.00
2	Feb	0	5		70		70	0.00	0	0.00
3	Mar	2	3		68		68	0.00	0	0.00
4	Apr	2	3		66		66	0.00	0	0.00
5	May	0	2	22	88	38	104	45.98	16	0.49
6	Jun	2	1		86		102	0.00	16	0.48
7	Jul	1	2		85		101	0.00	16	0.48
8	Aug	0	1		85		101	0.00	16	0.48
9	Sep	3	1		82		98	0.00	16	0.48
10	Oct	0	2		82		98	0.00	16	0.48
11	Nov	0	1		82		98	0.00	16	0.48
12	Dec	2	1		80		96	0.00	16	0.48
	Sums	12	31	22		38				3.85

Single Exponential	Part Category	Part Number	Unit Cost	Starting Inventory (SI)	$Prob_{Stockout}$ Proposal	$Prob_{Stockout}$ Current (Rc)	Total Cost (CP_{NPV})	Carrying cost [r]	Inflation (i)	Reject Ho:
	CONS-H-S	F1815/WW/RS	$17.20	105	0.0%	8.3%	$3,341.58	0.3	0.04	No

No. Period n	Month	Actual Value Xi	Forecast Value Fi	Replenish Proposal Rp	Ending Inventory Ep=SI-Xi+Rp	Replenish Current Rc	Ending Inventory Ec=SI-Xi+Rc	Purchase Cost CP($)	Differences D Ec-Ep	Cost of Difference D_{NPV}($)
1	Jan	16	20		89		89	0.00	0	0.00
2	Feb	20	18		69		69	0.00	0	0.00
3	Mar	6	19		63		63	0.00	0	0.00
4	Apr	17	15		46		46	0.00	0	0.00
5	May	10	16		36		36	0.00	0	0.00
6	Jun	30	14	102	108	91	97	1,535.16	-11	-4.46
7	Jul	22	19		86		75	0.00	-11	-4.44
8	Aug	7	20		79		68	0.00	-11	-4.43
9	Sep	20	16		59		48	0.00	-11	-4.41
10	Oct	26	17		33		22	0.00	-11	-4.40
11	Nov	13	20		20		9	0.00	-11	-4.38
12	Dec	17	18		3		-8	0.00	-11	-4.37
	Sums	204	211	102		91				-30.90

Single Exponential	Part Category	Part Number	Unit Cost	Starting Inventory (SI)	Prob$_{Stockout}$ Proposal	Prob$_{Stockout}$ Current (Rc)	Total Cost (CP_{NPV})	Carrying cost [r]	Inflation (i)	Reject Ho:
	CONS-H-C	MS24665-134	$0.13	450	8.3%	0.0%	$471.75	0.3	0.04	Yes
No. Period n	**Month**	**Actual Value Xi**	**Forecast Value Fi**	**Replenish Proposal Rp**	**Ending Inventory Ep=SI-Xi+Rp**	**Replenish Current Rc**	**Ending Inventory Ec=SI-Xi+Rc**	**Purchase Cost CP($)**	**Differences D Ec-Ep**	**Cost of Difference D_{NPV}($)**
1	Jan	222	267	267	495	650	878	84.22	383	1.24
2	Feb	85	249		410		793	0.00	383	1.24
3	Mar	251	183		159		542	0.00	383	1.23
4	Apr	257	210	642	544	650	935	83.40	391	1.25
5	May	328	229		216		607	0.00	391	1.25
6	Jun	284	269		-68		323	0.00	391	1.25
7	Jul	322	275	772	382	650	651	82.59	269	0.85
8	Aug	42	294		340		609	0.00	269	0.85
9	Sep	337	193		3		272	0.00	269	0.85
10	Oct	326	251	737	414	650	596	81.78	182	0.57
11	Nov	146	281		268		450	0.00	182	0.57
12	Dec	336	227	508	440	650	764	81.25	324	1.01
	Sums	2936	2926	2660		2600				12.17

Single Exponential	Part Category	Part Number	Unit Cost	Starting Inventory (SI)	Prob$_{Stockout}$ Proposal	Prob$_{Stockout}$ Current (Rc)	Total Cost (CP_{NPV})	Carrying cost [r]	Inflation (i)	Reject Ho:
	REP-H-C	ZP650-SC-M-B-3	$1,923.08	5	25.0%	25.0%	$212,555.89	0.3	0.04	Yes
No. Period n	**Month**	**Actual Value Xi**	**Forecast Value Fi**	**Replenish Proposal Rp**	**Ending Inventory Ep=SI-Xi+Rp**	**Replenish Current Rc**	**Ending Inventory Ec=SI-Xi+Rc**	**Purchase Cost CP($)**	**Differences D Ec-Ep**	**Cost of Difference D_{NPV}($)**
1	Jan	17	5	5	-7	5	-7	9,584.01	0	0.00
2	Feb	8	6	6	-9	13	-2	24,837.11	7	334.35
3	Mar	0	6	6	-3	5	3	9,521.56	6	285.65
4	Apr	3	6	6	0	8	8	15,184.79	8	379.62
5	May	1	5	5	4	6	13	11,351.43	9	425.68
6	Jun	4	5	5	5	9	18	16,971.59	13	612.86
7	Jul	6	5	5	4	11	23	20,675.37	19	892.80
8	Aug	2	5	5	7	7	28	13,114.12	21	983.56
9	Sep	0	5	5	12	5	33	9,336.66	21	980.35
10	Oct	9	4	4	7	14	38	26,057.35	31	1,442.46
11	Nov	8	5	5	4	13	43	24,117.16	39	1,808.79
12	Dec	7	5	5	2	12	48	22,189.35	46	2,126.48
	Sums	65	62	62		103				10,272.59

Moving Average	Part Category	Part Number	Unit Cost	Starting Inventory (SI)	Prob$_{Stockout}$ Proposal	Prob$_{Stockout}$ Current (Rc)	Total Cost (CP_{NPV})	Carrying cost [r]	Inflation (i)	Reject Ho:
	REP-H-S	2-1517	$3,762.29	10	0.0%	0.0%	$604,365.59	0.3	0.04	Yes
No. Period n	**Month**	**Actual Value Xi**	**Forecast Value Fi**	**Replenish Proposal Rp**	**Ending Inventory Ep=SI-Xi+Rp**	**Replenish Current Rc**	**Ending Inventory Ec=SI-Xi+Rc**	**Purchase Cost CP($)**	**Differences D Ec-Ep**	**Cost of Difference D_{NPV}($)**
1	Jan	0	2	2	12	10	20	37,500.10	8	726.56
2	Feb	1	2	2	13	11	30	41,115.50	17	1,553.51
3	Mar	3	2	2	12	13	40	48,432.49	28	2,607.90
4	Apr	2	2	2	12	12	50	44,561.04	38	3,527.75
5	May	4	2	2	10	14	60	51,818.24	50	4,603.50
6	Jun	3	2	2	9	13	70	47,959.93	61	5,591.48
7	Jul	3	2	2	8	13	80	47,803.43	72	6,584.46
8	Aug	1	2	2	10	11	90	40,317.07	80	7,364.74
9	Sep	6	2	2	6	16	100	58,451.65	94	8,607.92
10	Oct	3	3	3	6	13	110	47,337.00	104	9,501.54
11	Nov	3	3	3	6	13	120	47,182.54	114	10,366.55
12	Dec	5	3	3	4	15	130	54,263.74	126	11,406.69
	Sums	34	28	28		154				72,442.60

Single Exponential	Part Category	Part Number	Unit Cost	Starting Inventory (SI)	$Prob_{Stockout}$ Proposal	$Prob_{Stockout}$ Current (Rc)	Total Cost (CP_{NPV})	Carrying cost [r]	Inflation (i)	Reject Ho:
	REP-L-C	622-2362-001	$181.29	4	25.0%	0.0%	$11,927.11	0.3	0.04	Yes
No. Period n	Month	Actual Value Xi	Forecast Value Fi	Replenish Proposal Rp	Ending Inventory Ep=SI-Xi+Rp	Replenish Current Rc	Ending Inventory Ec=SI-Xi+Rc	Purchase Cost CP($)	Differences D Ec-Ep	Cost of Difference D_{NPV}($)
1	Jan	0	1	1	5	4	8	722.79	3	13.55
2	Feb	4	1	1	2	8	12	1,440.87	10	45.03
3	Mar	7	1	1	-4	11	16	1,974.73	20	89.76
4	Apr	1	2	2	-3	5	20	894.68	23	102.89
5	May	0	2	2	-1	4	24	713.41	25	111.47
6	Jun	0	1	1	0	4	28	711.08	28	124.44
7	Jul	0	1	1	1	4	32	708.76	31	137.32
8	Aug	0	1	1	2	4	36	706.44	34	150.12
9	Sep	1	1	1	2	5	40	880.17	38	167.23
10	Oct	1	1	1	2	5	44	877.30	42	184.23
11	Nov	1	1	1	2	5	48	874.44	46	201.12
12	Dec	0	1	1	3	4	52	697.27	49	213.54
	Sums	15	14	14		63				1,540.70

Moving Average	Part Category	Part Number	Unit Cost	Starting Inventory (SI)	$Prob_{Stockout}$ Proposal	$Prob_{Stockout}$ Current (Rc)	Total Cost (CP_{NPV})	Carrying cost [r]	Inflation (i)	Reject Ho:
	REP-L-S	DH1030-24-600	$1,658.78	4	0.0%	0.0%	$104,011.90	0.3	0.04	Yes
No. Period n	Month	Actual Value Xi	Forecast Value Fi	Replenish Proposal Rp	Ending Inventory Ep=SI-Xi+Rp	Replenish Current Rc	Ending Inventory Ec=SI-Xi+Rc	Purchase Cost CP($)	Differences D Ec-Ep	Cost of Difference D_{NPV}($)
1	Jan	0	1	1	5	4	8	6,613.46	3	124.00
2	Feb	0	1	1	6	4	12	6,591.88	6	247.20
3	Mar	1	1	1	6	5	16	8,212.96	10	410.65
4	Apr	0	1	1	7	4	20	6,548.93	13	532.10
5	May	1	1	1	7	5	24	8,159.45	17	693.55
6	Jun	5	1	1	3	9	28	14,639.09	25	1,016.60
7	Jul	0	1	1	4	4	32	6,485.03	28	1,134.88
8	Aug	2	1	1	3	6	36	9,695.81	33	1,333.17
9	Sep	0	1	1	4	4	40	6,442.78	36	1,449.63
10	Oct	0	1	1	5	4	44	6,421.75	39	1,565.30
11	Nov	0	1	1	6	4	48	6,400.80	42	1,680.21
12	Dec	3	1	1	4	7	52	11,164.85	48	1,913.97
	Sums	12	12	12		60				12,101.27

Bibliography

Abbas, K. and M. Hirofumi. "Forecasting and Inventory Management of Short Life Cycle Products." Journal of Operations Research, 44: 131-150 No.1 (1996).

Abouzolof, T. and D. Ireland. "Effective Supply-Chain Planning Secures Competitive Edge." Logistics Focus. Vol. 5: 2-9 (May 1997)

Adams, J., J. Abell and K. Isaacson. Modeling and Forecasting the Demand for Aircraft Recoverable Spare Parts. Santa Monica CA: The RAND Corporation, August 1993, (RAND-R-4211-AF/OSD).

Aviation Management Software, "EQUALS." http://www.equals.net/products.htm. (December 1997).

Ballou, R. Business Logistics Management. Logistics Strategy and Planning. New York: Prentice-Hall, Inc, 1992.

Banks, J., J. Carson and B. Nelson. Discrete-Event System Simulation. New York: Prentice Hall, Inc, 1995.

Bardi, E. J., T. Raghunathan and K. Prabir. "Logistics Information Systems: The Strategic Role of Top Management." Journal of Business Logistics, 15: 71-83 No.1 (1994).

Bienstock, C. "Sample Size Determination in Logistics Simulations." International Journal of Physical Distribution and Logistics Management, 26: 43-50 No. 1 (1996).

Brown, B. Characteristics of Demand for Aircraft Parts. Santa Monica CA: The RAND Corporation, 1956 (USAF R-292).

Brown, B. and A. Geisler. Analysis of Demand Patterns for B-47 Airframe Parts at Air Base Level. Santa Monica CA: 1954 (RAND-RM-1297).

Boylan, J. and F. Johnston. "Variance Laws for Inventory Management." International Journal of Production Economics, 45: 343-352 (August 1996).

Bohórquez, Col Rodrigo. Colombian Air Force Purchasing Agency Director. ACOFA/JET, Fort Lauderdale FL, Telephone Interview, 15 September 1997.

Butler, J. EQUALS Software Engineer. Fort Lauderdale FL, Telephone Interview, 10 January 1998.

Casper, C. "Warehousing and Logistics." Beverage World 116: 175-178 (15 March 1997).

Clay, G. and F. Grange. "Evaluating Forecasting Algorithms and Stocking Level Strategies Using Discrete-Event Simulation." Proceedings of the 1997 Winter Simulation Conference: 817-823 (1997).

Closs, D., T. Goldsby and S. Clinton. "Information Technology Influences on World Class Logistics Capability." International Journal of Physical Distribution and Logistics Management, 27: 4-17 No. 1 (1997).

Christensen, Maj Bruce and Capt Russell Ewan. "An Introduction to Repairable Inventory Models and Theory," US Air Force Document: 1-25 (November 1985).

Cooper, D. and W. Emory. Business Research Methods. New York: McGraw-Hill Companies, Inc, 1995.

Dane, F. Research Methods. Mercer University: Brooks / Cole Publishing Company, 1990.

Dussault, Capt Christian. Evaluation of Air Force and Navy Demand Forecasting Systems. MS Thesis, AFIT/GL/LAL/97M-1. School of Logistics and Acquisition Management, Air Force Institute of Technology (AU), Wright-Patterson Air Force Base OH, March 1995 (AD-A285299).

Emmet, I. "Main Characteristics of the Colombian Air Force Aviation Management Software EQUALS." E-mail file, Izaemmet@artdeco.modernism.com. January 6, 1998.

Fisher, G. Cost Considerations In System Analysis. Santa Monica CA: The RAND Corporation, American Elsevier Publishing Company, 1970 (R-490-ASD).

Fuerza Aérea Colombiana (FAC). Así Se Va a las Alturas, Historia de la Fuerza Aérea Colombiana. Imprenta Fuerzas Militares (1985).

-----. EMA3 03-98 Reporte Anual de Actividades Periodo 1990 a 1996. Bogotá: Comando Fuerza Aérea, Departamento EMA-3, 1998.

-----. JET 02-95 Reporte Anual del Area Logística. Bogotá: Comando Fuerza Aérea, Jefatura Técnica: 1-4, 1995.

-----. JET 01-97 Resumén Principales Necesidades del Area Logística en la Fuerza Aérea. Bogotá: Comando Fuerza Aérea, Jefatura Técnica, 1997.

-----. JOA 12-97 Reporte de Operaciones Aéreas. Bogotá: Comando Fuerza Aérea, Jefatura de Operaciones Aéreas: 2-10, 1997.

-----. Manual de Mantenimiento de la Fuerza Aérea Colombiana. DIMAN, Ultima Edición. Bogotá: Comando Fuerza Aérea, 1994.

Gil, Gen Hector. Colombian Air Force Attaché in The United States of America, Washington DC. Personal Interview, March 1998.

Krajeswski, L. and L. Ritzman. Operations Management: Strategy and Analysis. Menlo Park CA: Addison-Wesley Publishing Company, 1996.

Korpela, J. and M. Tuominen. "Inventory Forecasting With a Multiple Criteria Decision Tool." International Journal or Production Economics, 45: 169-178 (August 1996).

Law, A. and D. Kelton. Simulation Modeling and Analysis. New York : McGraw-Hill Series in Industrial Engineering and Management Science, 1991.

Lewis, I. and A. Talalayevsky. "Logistics and Information Technology: A Coordination Perspective." Journal of Business Logistics, 18: 141-157 No.1 (1997).

Makridakis, S., S. Wheelwright and R. Hyndman. Forecasting, Methods and Applications. New York: John Wiley and Sons, Inc, 1998.

Makridakis, S., S. Wheelwright and V. McGee. Forecasting Methods and Applications. New York: John Wiley & Sons, Inc, 1983.

Martin, J. "Plan for the Future," Manufacturing Systems 15: 54-58 (January 1997).

Mecham, M. "Allied Signal Exploits Software to Improve Parts Forecasts," Aviation Week and Space Technology 147: 78-79 No. 19 (November 1997).

Meléndez, Gen Alberto. Colombian Aeronautical Industry Corporation's CEO. Personal Interview, 15 December 1997.

-----. Colombian Aeronautical Industry Corporation's CEO. Bogotá, Colombia Telephone Interview, 20 June 1998.

Meléndez, Lt Col Daniel. Propuesta Organizacional de la Industria Aeronáutica Como Estrategia Ofensiva Para Afrontar los Retos del Siglo XXI en la Fuerza Aérea Colombiana. Tesis, IMA/FAC. Instituto Militar Aeronáutico, Fuerza Aérea Colombiana, Noviembre 1996.

-----. "Reingeniería o Gerencia de la Calidad en el Area de Mantenimiento Aeronáutico," Revista Fuerzas Militares de Colombia, 154: 54-59 (Septiembre 1995).

Mentzer, J. and J. Firman. "Logistics Control Systems in the 21st Century," Journal of Business Logistics, 15: 215-227 No.1 (1994).

Montgomery, C. Design and Analysis of Experiments. New York: John Wiley and Sons, Inc, 1997.

Neter, J., W. Wasseman and G. Whitmore. Applied Statistics. Boston MA: Allyn and Bacon, Inc. 1978.

Razzaque, M. A. "Challenges to Logistics Development: The Case of a Third World Country – Bangladesh," International Journal of Physical Distribution and Logistics Management, 27: 18-38 No.1 (1997).

Refik, G. "On the Value of Information in Dynamic Production/Inventory Problems Under Forecast Evolution," Journal of Naval Research Logistics, 43: 289-303 (1996).

Sanders, N. R. Measuring Forecast Accuracy: Some Practical Suggestions," Production an Inventory Management Journal, First Quarter: 43-46 (1997).

Sanders, N. R. "The Status of Forecasting in Manufacturing Firms," Production and Inventory Management Journal, Second Quarter: 32-35 (1997).

Sengupta, S. and J. Turnbull. "Seamless Optimization of the Entire Supply Chain," IIE Solutions, 28: 28-33 (October 1996).

Silver, E., D. Pyke and R. Peterson. Inventory Management and Production Planning and Scheduling. New York: John Wiley and Sons Inc, 1997

Sherbrooke, C. Optimal Inventory Modeling of Systems. New York: John Wiley and Sons Inc, 1992.

Suárez, Lt Col Carlos. Flying Hour Program. A Model Approach for the Colombian Air Force. MS Thesis, Naval Post Graduate School, Monterey CA, June 1995 (ADA301358).

-----. Colombian Air Force Purchasing Agency Director. Personal interview. 25 June 1998.

Tersine, R. Principles of Inventory and Materials Management. New York: Prentice Hall, 1994.

Vita

Lieutenant Colonel Daniel Melendez was born on [redacted] in [redacted] He graduated from the Emmanuel D'Alzon High School in 1975. He received a Bachelor of Science degree in Aeronautics Administration in 1996, from the Colombian Aeronautic Military Institute. He received his commission and Undergraduate Pilot Training on 1 December 1978 upon graduation from The Colombian Aviation Military School. He received his promotion to be a Lieutenant Colonel in 1996.

His first flying assignment was at "Comando Aéreo de Combate No.1" (Combat Air Command No.1) as a Fighter Pilot Student, in T-37. Later he flew A-37B and became a T-37 and A-37 instructor. In 1984 he flew Mirage 5. In January 1988, he was assigned to be a Kfir C-7 pilot and received his flying training at the Israeli Air Force. In January 1990, he was assigned at a C-130 flying program.

As a part of his logistics background, the most important assignments during his career were the following: In 1990 he was assigned to the CAF Logistics Headquarters as a Program Manager. Later, in 1992 he was assigned as a C-130 Technical Group Commander at the "Comando Aéreo de Transporte Militar". Then, in 1996 he was assigned as a Maintenance Group Commander at the "Comando Aéreo de Mantenimiento". In May 1997, he entered the Logistics Management Program, Air Force Institute of Technology. His follow-on assignment is to the Colombian Air Force Headquarters.

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13. ABSTRACT (*Maximum 200 Words*)

The Colombian Air Force recently installed a logistics operating system to improve the logistics system. However, the inventory cost and turnover have not stopped growing; subsequently, the operational readiness has been affected. The purpose of the study was to compare the performance of several forecasting techniques to improve the current planning process of spare parts in the CAF. The research used five phases.

The first and second phase identified the relevant factors and the forecasting techniques selected for the experiment. The factors were repairability, demandability and uniqueness. The forecasting methods were single and double exponential, moving average, autoregression and linear regression. The third and fourth phases simulate additional demand data. It was found that single exponential and moving average performs better than the others. The fifth phase found that the forecasting system can provide substantial savings to the logistics system. Finally, it can be concluded that demand for most spare parts cannot be predicted because forecasts always contain errors. It is necessary to consider additional improvements in logistics operations to make it easier to live with demand uncertainty. Among such improvements would be a shortening of the resupply time, the procurement lead time, and of the repair cycle for spare parts.

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