FORECASTING THE CONSUMABLE SPARES IN INTEGRATED MATERIALS MANAGEMENT ONLINE SYSTEM (IMMOLS) IN INDIAN AIR FORCE: MODELS FOR IMPROVING THE ACCURACY

A dissertation submitted to the Panjab University for the award of Master of Philosophy in Social Science partial fulfillment of the requirement for the 45th Advanced Professional Programme in Public Administration (APPPA)

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CONTENTS

CERTIFICATE

I have the pleasure to certify that Air Cmde K Shyam Sunder has pursued his research work and prepared the present dissertation titled **"Forecasting the Consumable spares in Integrated Material Management Online System (IMMOLS) in Indian Air Force: Model for Improving the Accuracy"** under my guidance and supervision. The dissertation is the result of his research and to the best of my knowledge, no part of it has earlier comprised any other monograph, dissertation or book. This is being submitted to the Punjab University for the degree of Master of Philosophy in Social Science in partial fulfillment for the Advance Professional Programme in Public Administration of Indian Institute of Public Administration (IIPA), New Delhi

I recommend that the dissertation of Air Cmde K Shyam Sunder is worthy for the consideration for the award of **M. Phil degree of Panjab University, Chandigarh.**

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DECLARATION

I, the undersigned, hereby declare this dissertation entitled, "Forecasting the Consumable spares in Integrated Material Management Online System (IMMOLS) in Indian Air Force : Model for Improving the Accuracy" is my own work and that all the sources I have accessed or quoted have been indicated or acknowledged by means of complete references/ bibliography. The dissertation has not been submitted for any other degree of this university or elsewhere.

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ABSTRACT

Considering the fact that IMMOLS has been operational for a little over one decade, it is felt necessary to find out whether it has provided the desired benefits that formed the basis of its conceptualization. The research is undertaken to ascertain the effectiveness of IMMOLS as an ERP platform and find out whether this online decision support system has provided desired strategic inputs for middle and top level management.

A reality check into the fleet serviceability status revealed that the average serviceability figures of ac are currently hovering between 55 to 60% while the percentage of Aircraft on Ground (AOG) incidence ranges between 20 to 35. This is way off the benchmark figure of 75 % serviceability as formulated by the policy makers in IAF. One of the major factor that has contributed to low tarmac availability of ac was non-availability of critical spare parts during the process of service, repair or overhaul. These incidences of non-availability were in general attributable either to Procurement bottlenecks or to Provisioning errors. Of the two, the aspect of procurement bottlenecks on account product obsolescence and diminishing manufacturing sources is well documented and researched. However, the issue of ascertaining the effectiveness of the provisioning models used in IMMOLS and feasibility of usage of alternative algorithms to generate better forecasts of spare parts has not been subjected to any scientific research.

Keeping the same in view the objectives of the study is finalized. The first objective is to undertake an in-depth analysis of the existing methodology of Provisioning of consumable spares. This is needed to ensure that what is documented is being followed. It is also necessary that the provisioning methodology incorporated is followed in IMMOLS.

Hence the second objective is to ascertain the accuracy and bias of the forecasting methodology adopted in IMMOLS. The methodology followed presently is the legacy of the British system. Hence it is important to see how this primitive method compares with modern forecasting models. Keeping this in mind, the third objective is to undertake a comparative analysis of the traditional forecasting models with the modern prediction techniques.

Based on the results of past research on aerospace components it is inferred that the current forecasting system adopted by IAF for consumable spares is modelled on Causal Forecasting Models (Cause effect relationship between flying effort and demand). Such models work well only for smooth and continuous demand and not with intermittent and erratic demand. This model has many inherent inconsistencies as future consumption does not always follow the past trends and is affected by many variable factors such as environment, the stresses and strains under which aircraft are operated and the technical practices followed in their maintenance. Further more,analysis of IMMOLS data as shown that consumption of spares is also affected by modifications on aircraft components which results in some spare parts being rendered unusable. The system of provisioning which has to rely mainly on forecasting has, therefore, to contend with such eventualities and face shortages and surpluses caused by these factors. Provisioning also gets distorted by changes in policy with regard to utilisation of aircraft and equipment, incorrect supply against indent and extent to which available assets are eroded by losses or damage to equipment, sudden failure in the functioning of components etc.

Keeping this in mind the following research hypothesis is formulated: - If the traditional model for forecasting of consumable spares based on program factors is replaced with modern prediction technique(s) then the service level of these ranges of spares would show a quantifiable improvement.

Towards this, extensive literature survey on forecasting trends is undertaken. The range of research papers ranged from 1956 to 2020. For the purpose of research secondary data of demand and flying effort pertaining to Akashdeep aircraft is extracted from IMMOLS front end, dashboard and query interfaces. For the purpose of testing of hypothesis, a Computer based Data Testing and Forecast modeling system on MS EXCEL platform has been developed. The program used inputs from Sample IMMOLS data, IBM SPSS and POM-QM test results and provided instantaneous correlation and forecasting performance results.

The research revealed that sufficient statistical evidence is available to reject the Null hypothesis as there exists very low correlation between Flying Effort and demand rate of consumable items. Besides very insignificant percentage of variability of demand can be attributed to variability in flying effort. In addition, it revealed that Demand pattern of ARS items show Normal distribution, while the Non-ARS items exhibit Poisson and Erratic distribution pattern thereby indicating a need for application of different forecast models, instead of the existing Program method, for achieving better accuracy. The Forecasting accuracy comparison test revealed that the current forecasting model (IMMOLS_CAR_FE) has significantly higher Minimum Absolute Standard Error (MASE) values relative to the other 5 models. Hence, it is inferred that sufficient statistical evidence was available to reject the Null hypothesis.

A road map for a paradigm shift in Provisioning in IAF purely based on mathematical and scientific presumptions has been attempted. It is suggested that Superior forecasting models may be incorporated in IMMOLS for getting better forecasting accuracy based on the distribution patterns of the item demands. The policy planners are urged to consider this research work a trigger for constituting a high-level committee for revision of Provisioning philosophy in the Indian Air Force.

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

ABBREVATIONS

AC	AIRCRAFT
AOG	AIRCRAFT ON GROUND
ARIMA	AUTO REGRESSIVE INTEGRATED MOVING AVERAGE
ARS	AUTOMATIC REPLENISHMENT SYSTEM ITEMS
CAR	CURRENT ANNUAL RATE OF CONSUMPTION
FE	FLYING EFFORT
FF	FORECAST FACTOR
IAF	INDIAN AIR FORCE
IMMOLS	INTEGRATED MATERIALS MANAGEMENT ONLINE SYSTEM
MAPE	MEAN ABSOLUTE PERCENTAGE ERROR
MdAPE	MEDIAN ABSOLUTE PERCENTAGE ERROR
MASE	MEAN ABSOLUTE SCALE ERROR
MSE	MEAN SQUARED ERROR
NON-ARS	NON-AUTOMATIC REPLENISHMENT SYSTEM ITEMS
POM QM	PRODUCTION AND OPERATION MANAGEMENT QUANTITATIVE METHODS
RMSE	ROOT MEAN SQUARE ERROR
SES	STANDARD EXPONENTIAL SMOOTHING
SPSS	STATISTICAL PACKAGE FOR SOCIAL SCIENCES

CHAPTER: I INTRODUCTION

1.1 The aerospace wars are short, sharp and technology intensive conflicts. They are distributed and conducted at lightning pace simultaneously across multiple theatres (Theatre is an operational area defined by the geographic combatant commander for the conduct or support of specific military operations) and geographically dispersed locations. Success within this environment is dependent not only on force projection operations but also on sustainment through simultaneous stabilization and reconstruction processes. The requirement to integrate “sustainment” and “force projection operations” in such a complex environment poses a great logistics challenge. The logistics and the supply chain structure that supports our forces on future battlefields, therefore, need to be an agile and responsive system, which provides timely support with maximum efficiency. It is in this context that the subject of spares supply chain in the IAF assumes great significance, since our aerospace assets are a conscious blend of State of Art fleets and Legacy systems.

1.2 Background and Context of Research

1.2.1 IAF Inventory Dynamics The inventory of Indian Air Force (IAF) in terms of its weapons, weapon delivery systems and associated spares is colossal. The inventory holdings are huge not only in terms of quantity but also in terms of physical distribution as the equipment is dispersed throughout the length and breadth of the country. Thus, effective management of materials, through stringent economical purchasing, reduction in inventory levels, decrease in inventory carrying costs, prevention of deterioration and speedy disposal of surplus and scrap is critical for sustenance of the weapon systems.

1.2.2 IMMOLS In order to fine-tune the complexities of supply chain management, IAF has migrated to an ERP based system named as Integrated Materials Management Online system (IMMOLS). IMMOLS is a Decision Support System that has ushered in a paradigm shift in the Logistics management process of the Indian Air Force. This audit enabled digital platform was operationalized in 2006 and has gone through a large number of modifications and platform upgrades during the past decade with a single-minded aim to fine-tune the complex logistics processes in IAF and ensure availability of the right spare in the right quantity at the right time. This e-logistics tool has acted as a game changer and has provided the fleet managers the much-needed inputs on asset visibility and optimal utilization of assets.

1.3 Research Problem

1.3.1 Area of Research Considering the fact that IMMOLS has been operational for a little over one decade, it is necessary today to find out whether it has provided the desired benefits that formed the basis of its conceptualization. Accordingly there is a need to ascertain the Effectiveness of IMMOLS as an ERP platform: Whether IMMOLS has been able to provide desired strategic inputs for middle and top level management and suggest improvement in the existing system. Considering the limitation of time and resources, it is well-nigh impossible to undertake research on the complete sub areas of IMMOLS. Hence this research is limited only to the aspect of Provisioning and Forecasting efficacy in IMMOLS.

1.3.2 Statement of the Problem Evaluating the efficacy of the Provisioning models in IMMOLS based on program factors by comparing the strength and nature of relationship between Flying effort and demand of consumable spares. Subsequently, determining an effective prediction technique for improving the forecasting accuracy of consumable spare parts**.**

1.3.3 Objectives

The objectives of the Study are:

- To undertake an in-depth analysis of the existing methodology of Provisioning of consumable spares.
- To ascertain the accuracy and bias of the forecasting methodology adopted in IMMOLS.
- To undertake a comparative analysis of the traditional forecasting models with the modern prediction techniques.

1.4 Research Design

The Research Strategy will be Quantitative and the Research Design will be Causal in nature. The Research Design is Causal as it is involved in extraction of IMMOLS Data of Flying unit consumption and establishes a correlation with the total flying effort.

1.5 Rationale or Justification

The average serviceability figures of ac are currently hovering between 55 to 60% while the percentage of Aircraft on Ground (AOG) incidence ranges between 20 to 35%. This is way off the benchmark figure of 75 % serviceability as formulated by the policy makers in IAF (Refer IMMOLS AOG data). One of the major factors that contribute to this low tarmac availability of ac is non-availability of critical spare parts during the process of service, repair or overhaul. Such incidences of non-availability are in general attributable either to Procurement bottlenecks or to Provisioning errors. Of the two, the aspect of procurement bottlenecks on account of product obsolescence and diminishing manufacturing sources is well documented and researched. However, the issue of ascertaining the effectiveness of the provisioning models used in IMMOLS and feasibility of usage of alternative algorithms to generate better forecasts of spare parts has been subjected to very limited research.

1.6 Research Questions

The research questions that have been formulated, based on the research objectives are-

- What is the level of accuracy of the existing/current system?
- Are the Provisioning models used in IMMOLS the correct/appropriate and relevant models for solving Indian Air Force's (IAF) inventory problem today?
- Is/are effective methodologies available for forecasting the demands for consumable items?

1.7 Hypothesis

Based on the Research Objectives and Research Questions, as formulated in the section 1.2, the Hypothesis has been formulated as under

1.7.1 Null Hypothesis

The Null hypothesis is as follows: -

The traditional model of forecasting of spares used in IMMOLS based on program factors provides the desired level of forecasting accuracy.

1.7.2 Alternate Hypothesis

Keeping the above objective in mind the following is the research hypothesis: -The modern prediction technique(s) will have better accuracy level in terms of forecasting the spares.

1.8 Conclusion

IAF has been procuring spares based on archaic provisioning methods given to us by the British. The accuracy of the present provisioning used by the IAF correlating the spares consumption with flying efforts has not been studied and analyzed subsequently. The shortage of critical aircraft spares at crucial times gives an indication that the present provisioning method needs detailed analysis.

CHAPTER: 2 LITERATURE REVIEW

2.1 Introduction

In this Chapter an exhaustive review of literature on Demand patterns of aerospace components, Inventory models and prediction techniques, Forecasting and Ordering of consumable spare parts that are practiced globally has been undertaken. A separate section has been dedicated to the forecasting model used in IAF to bring out the linkages and inconsistencies. This has helped in identifying the research gap in the context of IAF and the area of contribution of this research work.

2.2 Demand Pattern for Consumable Spare Parts.

2.2.1 Demands for most aerospace components & spares parts that are of consumable nature tend to be non-linear. This non-linearity also, in many cases, falls in erratic domain. Even if the demand rate of a particular part is known for some past period, the future demand during a similar period cannot be predicted with similar accuracy. This occurs since a large number of components in aging systems break down more often and in unexpected ways. These causes include corrosion, damage, fatigue, cracking and wear and tear amongst other factors. When a system passes into aging phase the original design assumptions begin to break down and the progressive damage types become more unpredictable. The fluctuations in demand pattern are therefore one of the factors to be taken into account for quality forecast. For the purpose of this study the focus is on forecasting techniques for erratic and slow moving demands as these are most difficult to predict and cause production holdups.

2.2.2 The demand pattern for an erratic item has so much random variation that in general no trend or seasonal pattern can be discerned. The two factors leading to an erratic demand pattern (Silver, 1970) are: -

- There may simply be a large number of small Users and a few large Users. Most of the transactions are small in magnitude as they are generated by the small Users, although occasionally one of the large Users places a large demand.
- In a multi-echelon system, a non-erratic demand pattern at the consumer level may be transformed into a highly erratic demand pattern by inventory decisions made at higher levels. This phenomenon, known as the bull-whip effect, arises when small variations in demand are magnified along the supply chain.

2.2.3 Bartezzaghi et al 1998, concluded:-

- In considering the numerousness of potential Users, and in particular the frequency of customer requests, lumpiness increases as the frequency of each customer order decreases. In fact, the lower the frequency of orders, lower the number of different users placing an order in a given time period.
- If there is a correlation between user demand lumpiness may occur even if there are a large number of Users. Correlation may be due to imitation which leads to sudden peaks in demand. In the case of the Royal Air Force, periodic exercises and operations are often correlated between aircraft.

2.2.4 Through examining a forecasting system similar to that operated by the Royal Air Force, (Foote, 1995) identifies a further cause of erratic demand as in large repair facilities, there is a tendency to repair a component once a quarter or once a year owing to the long lead-times for spare parts or to reduce costs by minimizing the number of setups.

2.2.5 In considering demand for spare parts as being generated by a failure process Beckmann suggests some further causes: -

- Multiple demands may occur through sympathetic replacement, whereby maintenance personnel discover a defective part on one aircraft and, as a result, inspect that item on other aircraft, replacing incipient failures.
- The aggregation of demand, or bucketing, pre-determines the level of intermittency in a given time series. What appears to be a smooth demand series at a quarterly aggregation may become decidedly erratic at a monthly or weekly aggregation.

2.2.6 In certain cases, even if demand has a lumpy history it may not be erratic. The lumps may be due to occasional extraordinary requirements from Users, as Brown, (1973) discovered in the case of an O-ring used in the boiler tubes of an aircraft carrier in the US Navy. The demand history for the O-ring showed single digit demands with an occasional demand for over 300 units interspersed by zeros; a classic erratic demand pattern. However, a closer examination revealed that 307 units were required for overhauls carried out in shipyards and these were scheduled up to two years in advance. Alternatively, a pre-determined array of spare parts may be required as fly-away detachment packs to accompany a squadron of aircraft on planned exercises. In such cases, it may be possible to include the requirements as scheduled demand, rather than having to forecast; all that would be necessary is an improvement in the flow of information.

2.2.7 An item is said to have an erratic demand pattern if the variability is large relative to the mean. After early research into erratic demand, (Brown, 1973) suggested an item should be classed as erratic if the standard deviation of the errors from the best-fitted forecast model is greater than the standard deviation of the original series. Under such circumstances, he recommends setting the forecast model as a simple average of the historic observations. Straightforward statistical tests were more recently used by Willemain et al. on actual data to gauge the level of intermittency, including: -

- The mean interval between transactions, or equivalently, the percentage of periods with positive demand.
- The degree of randomness in the data. Forecasting requirements are lowered if the demands are a fixed size or the transactions occur at fixed intervals. Thus, the coefficient of variation (CV), which expresses the standard deviation as a proportion of the mean, for the demand size and interval length are useful statistics.
- Most research on erratic demand assumes independence between successive demand sizes and successive demand intervals, as well as independence between the sizes and intervals. In fact, some substantial positive and negative autocorrelations and cross-correlations were found in their data.

2.3 Inventory Models

2.3.1 An inventory control policy for low demand was possibly considered first by Whitin and Youngs in 1955, for a simple Poisson situation, and developed slightly by Heyvaert and Hurt in 1956. In cases of continuous review with convex holding costs and fixed replenishment costs, Beckmann in 1962 proved the optimality of an (s,S) inventory policy, whereby an order is placed to raise the available stock (on hand plus on order minus backorders) to an order-up-to level S when the stock level falls to or below reorder point s. The model considered an arbitrary distribution for the intervals between demands and a distribution for the demand sizes that is independent of the previous demand size but may depend on the elapsed time since the last demand.

2.3.2 An important paper on erratic demand is the 1972 paper of Croston who demonstrated that using simple exponential smoothing forecasts to set inventory levels could lead to excessive stock levels. He argues that exponential smoothing places most weight on the more recent data and therefore gives estimates that are highest just after a demand, and lowest just before a demand. The replenishment quantity is likely to be determined by the biased estimates that immediately follow a demand as a consequence. By way of solution, Croston suggested that unbiased forecasts are needed for stock replenishment decisions immediately after a transaction occurs, and should be based on separate forecasts of the demand size and the interval between transactions. The method proposed by Croston is seen to reduce the bias associated with exponential smoothing. Other authors have assumed particular demand distributions, usually a compound distribution arising from combining distributions for transaction occurrence and demand size. In this manner, the total number of units demanded over a lead-time can be considered as the sum of a random number of demands, each generating a random demand size.

2.3.3 The compound Poisson distribution where transactions are assumed to arrive in accordance with a stationary Poisson process, as developed by Adelson in 1966, has frequently found favour in the literature. An (s,S) policy is normally superior to a (Q,r) policy where a fixed quantity Q is ordered when the stock level falls to or below reorder point r, in terms of reduced total holding and replenishment costs. In fact, as the demand pattern becomes more erratic in nature, an (s,S) system increases in superiority and this tends to be the preferred method for consideration. An order-up-to level is intuitively appealing for an erratic demand item as the amount by which the reorder point is passed may vary widely between one replenishment requirement and the next. However, the computational complexity of determining the optimal order-up-to value sometimes restricts its use in favour of a fixed order quantity. Recursive expressions for determining optimal parameters for an (s,S) policy under periodic review with discrete compound Poisson demand and constant lead-time were provided by Veinott and Wagner in 1965 and improved by Bell in 1970, while Archibald and Silver consider the analogous case of continuous review in 1978. A compound Poisson demand process with stochastic lead time is considered in 1977 by Dirick and Koevoets who use Markov renewal theory to give very complex formulae for an (s,S) policy. Markov renewal theory was previously used in 1975 by Kao, although his methodology assumed zero lead-time while allowing arbitrary demands size and interval distributions. Also in 1977, Bott considered three compound Poisson distributions where the selected demand size distribution depended on the variability in the historical data. Bott suggests that as the negative binomial distribution has a variance-to-mean ratio (VMR) greater than unity for any choice of parameters, the demand size may be modeled by such a distribution if the sample data has a VMR greater than one. Similarly, the Poisson distribution may be suitable if the sample VMR is equal to one and the binomial distribution if it is less than one. When combined with Poisson transaction arrivals, demand sizes with a geometric probability distribution provides a demand distribution referred to as stuttering Poisson (sP), as described by Sherbrook in 1966. As a special type of compound Poisson distribution, the sP distribution has remained a popular choice in the erratic demand environment. Silver et al. in their paper of 1971 considered an sP demand pattern for an (s,S) inventory policy with continuous review. In his paper of 1978, Ward used an approximate regression model to calculate reorder points based on a fixed service level, although no attempt is made to minimize the total operating cost. A (Q,r) inventory policy with continuous review is utilised. The model assumes constant lead-times and demand is modelled by the sP distribution. A regression model was also used by Mak and Hung in 1986 for computing optimal (s,S) policies where the lead-time demand is modelled by an sP distribution and the lead-time itself is assumed constant. In their paper of 1971, Foster studied the effect of demand distributions on optimal decisions and costs for a (Q,r) inventory policy. Using an (s,S) policy Naddor in 1978 also examined how optimal decisions and costs are affected by different demand distributions, different shortage costs and different lead-times. Numerical solutions imply that the precise form of the distribution of demand is not essential for the determination of optimal decisions in the system. Where the standard deviation is relatively small compared to the mean, the decisions are hardly affected by the form of the distribution because of the relative flatness of the total cost around the optimum. However, when the standard deviation is relatively large compared to the mean, the decisions and costs are more sensitive to the form of the distribution. Methods that assume lead-time demand can adequately be approximated by the normal distribution, in general, cannot be utilised for erratic and slow-moving line items and alternatives are required. A particular problem in the case of erratic demand is that the actual stock level when reordering takes place will not be r but some level below r as one transaction may cause the stock level to fall significantly.

2.4 Developments in Forecasting Models

2.4.1 In 1972 Croston demonstrated his forecasting method to be superior to exponential smoothing (ES) when assuming the intervals between transactions follow the geometric distribution (demand occurs as a Bernoulli process), their size is normally distributed, and the intervals and sizes are independent of each other. Willemain, in 1994 violated these assumptions in generating a comparative evaluation between Croston's method and ES. Various simulated scenarios covered a log normal distribution of demand size, and both positive and negative autocorrelations and cross-correlations in the intervals and sizes. Through making comparisons only at times of positive demand, in all cases Croston's method was found to provide more accurate estimates of the true demand. The authors concluded that Croston's method is quite robust and has practical value beyond that claimed in Croston's original paper. However, an important observation was the fact that results from industrial data showed very modest benefits as compared to the simulation results. The usefulness of Croston's method was also investigated by Johnston and Boylan in 1996. A simulation analysis was conducted to determine the minimum interval between transactions that was required for a modification of Croston's method to outperform ES. Using a Poisson arrival process and a number of demand size distributions, comparisons were made between the errors observed at every point in time and only after a demand occurred. It was observed that the modified method outperformed ES when the average interval between demands is greater than 1.25 periods and the greater the interval the more marked the improvement. In addition, longer forecasting horizons were seen to improve the relative performance of the method while any variability in the demand size has only a small effect on the improvement.

2.4.2 Syntetos and Boylan in 1998 quantified the bias associated with Croston's method through simulation, while in a second paper of 1998 the same authors provided three modifications to Croston's method that attempt to give unbiased estimates of the demand per period. They indicate that Croston's estimates of the demand size and the interval between transactions are determined to be correct; it is an error in their combining which fails to produce accurate estimates of the demand per period. Wright in 1986 provided an extension to Holt's two-parameter smoothing method for the case of intermittent data. Consideration is given to time series which naturally occur at irregular time intervals, such as the inventory applications covered in this research, as well as cases where the frequency of reporting changes from annual to quarterly, for example, or where occasional data observations are simply unavailable in an otherwise regularly spaced series. In many applications, the extended procedure requires only about twice the resources of the regular Holt's method. Sani and Kingsman in 1997 compared periodic inventory control policies and demand forecasting methods in an attempt to determine which are best for slow-moving and erratic demand items. Periodic systems are put forward as preferred by stock controllers due to the convenience of regular ordering days for the stockist, as well as for the supplier who can plan efficient delivery routes. Ten periodic inventory policies are compared using real-world data from a spare parts depot and in each case five demand forecasting methods are used to determine values for s and S. The comparisons include simple rules developed by practicing stock controllers which relate alternative sets of (s,S) values to ranges of annual demands and the value or criticality of the item. Using two performance measures, namely annual inventory cost and the proportion of demands satisfied immediately from stock, the authors conclude that a 52-week moving average forecasting method is best, followed closely by Croston's method.

2.4.3 Tomas Eloy Salais-Fierro, Jania Astrid Saucedo-Martinez, Roman Rodriguez-Aguilar and Jose Manuel Vela-Haro in their study in January 2020 focused on the study of qualitative and quantitative variables when making demand projections by using fuzzy logic and artificial neural networks. In their study of the automotive industry, they built a hybrid method for integrating demand forecasts generated from expert judgments and historical data. Demand forecasts were prepared through the integration of variables; expert judgments and historical data using fuzzy logic and neural network. The methodology included the integration of expert and historical data applying the Delphi method as a means of collecting fuzzy data. The result according to proposed methodology showed how fuzzy logic and neural networks is an alternative for demand planning activity. In their study, qualitative and quantitative variables were integrated through the implementation of fuzzy logic and time series artificial neural networks.

2.4.4 Makridakis et al. (2018) in their research did a comparison of Statistical and Machine Learning forecasting methods. Their aim was to research the validity of the Machine Learning (ML) methods, which have been proposed in the academic literature as alternative to Statistical ones for time series forecasting. After comparing the post sample accuracy of popular ML methods with that of eight traditional statistical ones, they found that the ML methods are dominated across the accuracy measures used and for all forecasting horizons examined. Moreover, it was also observed that their computational requirements are considerably greater than those of statistical methods. The authors also discuss and explain why the accuracy of ML models is below that of statistical ones and proposes some possible ways forward.

2.5 Forecasting Accuracy Metrics for Intermittent Demands

2.5.1 In order to evaluate forecasting accuracy, there are a number of measures that are in vogue. The global trends and usages are being highlighted in the succeeding paragraphs. One measure commonly used in inventory control is the Mean Absolute Deviation (MAD), calculated simply as the average of the absolute forecast errors

$$\mathbf{MAD} = \frac{\sum_{i=1}^{n} \left| xi - \bar{x} \right|}{n}$$

xi : Performance Value for Period i

$\bar{x}$: Average Value

n : Number of Data

2.5.2 A desirable feature of MAD is that it is less affected by outliers than other measures, which Wright et al(1988) noted as being of particular importance in practical forecasting situations where outliers are a frequent occurrence. Kling and Bessler (1981) suggest that if large errors do in fact have a greater than proportional cost compared to small errors then a measure that places a heavier penalty on large errors is more appropriate. The Mean Square Error (MSE) and the Root Mean Square Error (RMSE) place more weight on large errors:

$$MSE = \frac{1}{N} \sum_{i=1}^{N} \left(f_i - y_i\right)^2$$

Where N is the number of data points,
f_i the value returned by the model and
y_i the actual value for data point i.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (\text{Predicted}_i - \text{Actual}_i)^2}{N}}$$

2.5.3 Mean square error measures have often been criticized as unreliable and sensitive to outliers. In addressing the reliability of these measures, Armstrong and Collopy examined the extent to which the RMSE produces the same accuracy rankings when applied to different samples taken from a set of data series, including quarterly and annual observations with differing periods looking ahead. They found that rankings based on the RMSE were highly unreliable except where the comparisons involved many series. None of these measures allow comparison across time series as they are all absolute measures related to the specific series. To objectively compare forecasts from different series with widely differing sizes Makridakis and Hibon suggest a unit free metric such as the Mean Absolute Percentage Error (MAPE) which relates the size of the error to the actual observation on a proportional basis:

$$MAPE = \frac{\sum_{t=1}^{n} \frac{|e_t|}{y_t} \times 100}{n}$$

2.5.4 MAPE also finds favour with Lawrence et al. (1986) for several reasons, "First, being less affected than squared measures by extreme errors, it becomes a good relative measure for comparisons among techniques. Secondly, the metric is independent of scale, enabling a comparison to be made between different time series. Additionally, it is a common measure used to assess relative accuracy". This measure also has its disadvantages. Armstrong and Collopy,1992 indicate that MAPE is only relevant for ratioscale data whereby the data has an absolute zero, as is the case for most economic data, and, as the method puts a heavier penalty on forecasts that exceed the actual value than those that are less, it is biased in favour of low forecasts. A further disadvantage of MAPE is identified by Gardner,1990 for time series similar to those encountered in this study; it is often left undefined due to zero observations in the series and is therefore sensitive to errors in such cases. All the measures mentioned thus far, except perhaps MAD, offer poor protection against outliers and a single observation may dominate the analysis because it has a much larger or smaller error than the other observations in the series. Armstrong and Collopy, 1992 suggest the effect of outliers can be reduced by trimming so as to discard high and low errors and an extreme way to trim is to use medians to remove all values higher and lower than the middle value. They recommend the median absolute percentage error (MdAPE) as a means for comparing methods when many series are available:

MdAPE = Observation $\frac{n+1}{2}$ if n is odd, or the mean ob observations $\frac{n}{2}$ And $\frac{n}{2}$ + 1 if n is even, where observations are ordered by APE.

2.5.5 The MdAPE reduces the bias in favour of low forecasts and therefore offers an additional advantage over MAPE. In the early part of this study the four measures of MAD, RMSE, MAPE and MdAPE are utilised for all forecast comparisons and, as there is some justification for each measure, the consistency of results between the measures is examined.

2.5.6 In recent past forecasting domain specialist, have been using a new Metric named Minimum Absolute Scaled Error (MASE). The MASE was proposed by Hyndman and Koehler (2006) as a generally applicable measurement of forecast accuracy without the problems seen in the other measurements. They proposed scaling the errors based on the in-sample MAE from the naïve forecast method. Using the naïve method, we generate one-period-ahead forecasts from each data point in the sample. Accordingly, a scaled error is defined as

$$q_t = \frac{e_t}{\frac{1}{n-1}\sum_{i=2}^{n} |y_i - y_{i-1}|}$$

2.5.7 The result is independent of the scale of the data. A scaled error is less than one if it arises from a better forecast than the average one-step, naïve forecast computed in sample. Conversely, it is greater than one if the forecast is worse than the average onestep, naïve forecast computed in-sample. The mean absolute scaled error formula is: -

$$\text{MASE} = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{|e_t|}{\frac{1}{T-1}\sum_{t=2}^{T} |y_t - y_{t-1}|}\right) = \frac{\sum_{t=1}^{T} |e_t|}{\frac{1}{T-1}\sum_{t=2}^{T} |y_t - y_{t-1}|}$$

2.6 Forecasting Techniques for Consumable Spares in IAF

IAF uses a programme method of forecasting for consumable spares. In this method (IAP 1541,1975, Leaflet 1) past issues of an item are related to the past programme activity which is assumed to have caused the demand e.g. flying hours, aircraft months, or equipment operating hours. Requirements are then projected according to the ratio of the past to the future programme. For this purpose, a forecast factor which establishes the relationship between the past flying effort and the planned future utilization of aircraft or equipment is worked out and applied to the annual consumption. For instance, if the issues of an item during the past 12 months were 100 for 1,000 hours of flying and the flying planned for the provisioning period is 5,000 hours, the forecast factor by which the past consumption is multiplied will be the ratio between the past flying and the future planned rate of effort. In the case of items for which consumption cannot be related to flying effort, e.g. ground and test equipment, ground radar sets, airmen's clothing and accoutrements, fire-fighting equipment, cook-house utensils etc., the forecast factor applied is the ratio between the actual holding of the main equipment or strength of personnel to the future planned holding or establishment. The Programme Method of calculations based on flying hours, aircraft months, equipment operating hours, landings or some similar measure, assumes that there is a direct relation between hours flown and the past consumption of an item; that the projected flying hours will be flown; and that in the future, there will be the same relation between hours flown and the consumption rate as in the past. This method does not take into consideration such factors as climatic conditions, maintenance capabilities and practices, design weaknesses, and the age of the inventory. Any of these can appreciably influence the usage rate of a particular part and cause it to fluctuate even when flying hours remain constant. However, this method is the only reliable and accurate means of calculating requirements of items whose usage can be related to one particular type of activity. For instance, an engine bearing may be subject to wear according to the hours the engine is operated. The programme method is used for computing requirements of specific to type aircraft spares. To ensure accuracy in programming of future requirements, the consumption data for such for such spares should normally be obtained from the units where the usage actually takes place. In the case of rotables, programme method provides the gross requirements for purpose of working out the anticipated wastages to be provisioned.

2.7 Conclusion

As is evident, the forecasting system of consumable spares is modelled on Causal Models (Cause effect relationship between flying effort and demand). Such models work well only for smooth and continuous demand and not for intermittent and erratic demand. This model used in IAF has many inherent inconsistencies as future consumption does not always – follow the past trends and is affected by many variable factors such as environment and the stresses and strains under which aircraft and equipment are operated and the technical practices followed in their maintenance. Furthermore, consumption of spares is also affected by modifications which results in spare parts being rendered unusable. The system of provisioning which has to rely mainly on forecasting has, therefore, to contend with such eventualities and face shortages and surpluses caused by these factors. Provisioning also gets distorted by changes in policy with regard to utilisation of aircraft and equipment, incorrect supply against indent and extent to which available assets are eroded by losses or damage to equipment, sudden failure in the functioning of components etc. **In absence of empirical research in this area,** IAF forecasting managers are continuing to use archaic forecasting models and thus unable to derive the benefit of modern forecasting models that can be embedded in IMMOLS and reduce forecast bias and thereby increase service levels of critical components. The focus is on this critical but hitherto neglected area for conducting this research to ascertain the efficacy of the current model and to formulate a suitable forecasting model that can be adopted by Indian Air Force.

CHAPTER: 3 RESEARCH METHODOLOGY AND DATA COLLECTION

3.1 Introduction

The Programme Method of calculations based on flying hours, assumes that there is a cause and effect relation between hours flown and the past demand of a consumable spare. It also assumes that the projected flying hours will be actually flown and that in the future, there will be the same relation between hours flown and the demand rate as in the past.

3.2 Research Hypothesis

Based on the results of past research on aerospace components it is inferred that the current forecasting system adopted by IAF for consumable spares is modelled on Causal Forecasting Models (Cause effect relationship between flying effort and demand). Such models work well only for smooth and continuous demand and not with intermittent and erratic demand. This model has many inherent inconsistencies as future consumption does not always follow the past trends and is affected by many variable factors such as environment, the stresses and strains under which aircraft are operated and the technical practices followed in their maintenance. Further more,analysis of IMMOLS data as shown that consumption of spares is also affected by modifications on aircraft components which results in some spare parts being rendered unusable. The system of provisioning which has to rely mainly on forecasting has, therefore, to contend with such eventualities and face shortages and surpluses caused by these factors. Provisioning also gets distorted by changes in policy with regard to utilisation of aircraft and equipment, incorrect supply against indent and extent to which available assets are eroded by losses or damage to equipment, sudden failure in the functioning of components etc. These leads to forecasting errors and affect the average serviceability figures of ac are currently hovering between 55 to 60% while the percentage of Aircraft on Ground (AOG) incidence range between 20 to 35. This is way off the benchmark figure of 75 % serviceability as formulated by the policy makers in IAF.

3.3 Null Hypothesis

Keeping the above in mind the following is the Null hypothesis: -

The traditional model of forecasting of consumable spares used in IMMOLS based on program factors provides the desired level of forecasting accuracy.

3.4 Alternate Hypothesis.

The Alternate hypothesis is as follows: -

The modern prediction technique(s) will have better accuracy level in terms of forecasting the spares.

3.5 Constructs

The two constructs are

3.5.1 Evaluating the IMMOLS forecasting model based on program factors by determining the **strength and nature of relationship** between Flying Effort and demand of consumable spares.

3.5.2 Comparative study and evaluation of **current forecasting model** with **modern prediction techniques**.

3.6 Research Design & Parameters

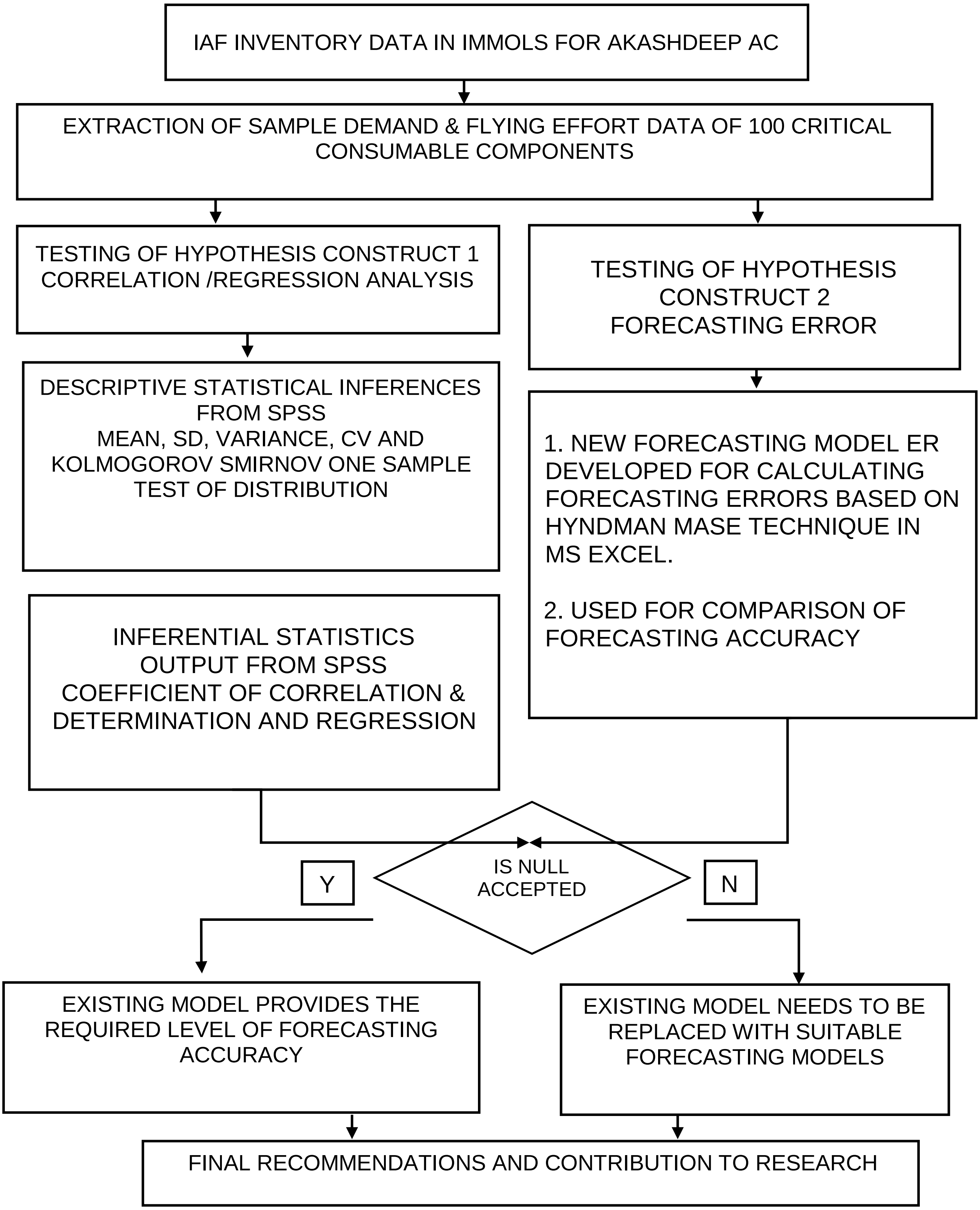
This is an original research undertaken by extracting authentic primary data from IMMOLS, using software extraction tools. The essential research parameters are as below: -

Type of Research	Diagnostic
Methods Used	Observation and examination of IMMOLS electronic records
Nature of Data	Secondary data collected directly from IMMOLS electronic transaction tables
Period	The Study period considered in present context ranging from 2014-15 to 2018-19. The data on various parameters have been collected over a period of 60 months for the study.
Sample Fleet	Akashdeep (Original name not disclosed due to security reasons.). The data has been collected from one of the fighter fleets of Indian Air Force.
Sample Data	E-Transaction records for last 60 months for 100 critical ARS and Non-ARS items of Akashdeep Fleet have been collected. With this data the total analysis has involved over 12000 data elements.
Data type	E-Records of Demand of all spares, monthly Flying effort of the aircraft, production holdups and Aircraft on Ground incidences, provisioning and procurement of spares and components.
Method of Sourcing data	Examination and extraction of the online data available in query screens, dashboards and front end interface of IMMOLS through export functionality.
Scope & Limitations	The scope of the research has been limited only to Forecasting of consumable spares of Akash deep aircraft. Forecasting of Repairables and Rotables has been kept out of the scope of this research due to paucity of time and limited access to data. Detailed analysis of inventory models has also been kept outside the purview of this study on account of inaccessibility of details of stocks, order and lead time.

3.7 Research Flow

The operational and statistical design of the research is depicted in the flow chart below: -

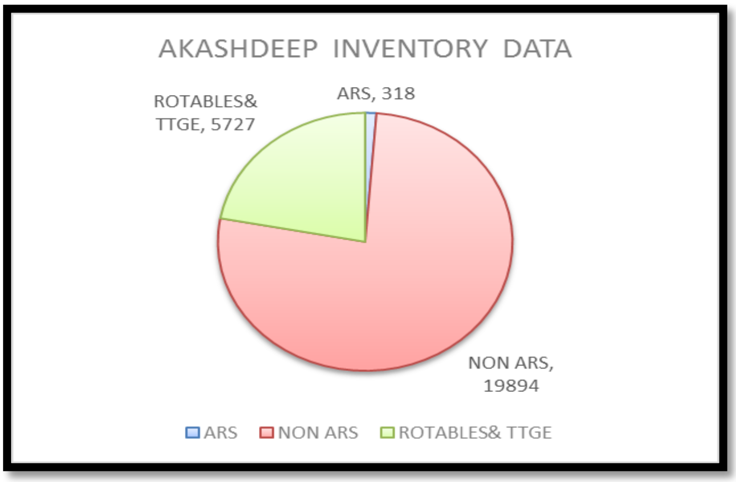
Figure 3.1 Research Flow



3.8 Data Collation

3.8.1 Population The total number of components and spares in the inventory of Akashdeep fleet amount to fifteen thousand nine hundred and thirty nine lines. The spread of Akashdeep ac spares is depicted in the pie chart below: -

Figure 3.2 Percentage Distribution of Akashdeep Inventory



Source: IMMOLS

3.8.2 Sample of Spares For the purpose of this research, a combination of stratified sampling and quota sampling by taking into consideration all system critical consumable spares that have shown susceptibility to production holdup and AOG incidences have been taken. Out of the entire lot of spares, the most critical spares (100) were identified using stratified sampling technique.

Table 3.1 Type of Spare

TYPE OF SPARE	NUMBER
ARS	100
NON-ARS	100 *Repairable Non-ARS has been excluded

3.8.3 Sampling of Dependent and Independent Variables.

Before proceeding for analysis, the following linear relationship between Flying Effort (Independent Variable) and Demand for each consumable item (Dependent Variable) has been considered, based on IAF Policies and Manuals. It is based on the presumption elucidated in the IAF policy manual (IAP 1541) issued in 1975. This study is aimed at verifying the linear relationship between Flying effort and demand.

$$Y = ax + b + e$$

Where y = Demand Qty (in numbers) = Dependent variable
x = Flying Effort (in hours) = Independent variable
e = Error Term

3.8.4 Demand Sample

For the purpose of this research, monthly demand data (Dependent Variable) for past 100 months have been extracted from IMMOLS. These demand figures have also been aggregated on a yearly basis for purpose of analysis at different points of this research.

Table 3.2 Period

PERIOD OF DEMAND	NUMBER
Apr 2014-15 – Mar 2018-19	60 months

Source - IMMOLS

3.8.5 Flying Effort Data (Refer Appendix C)

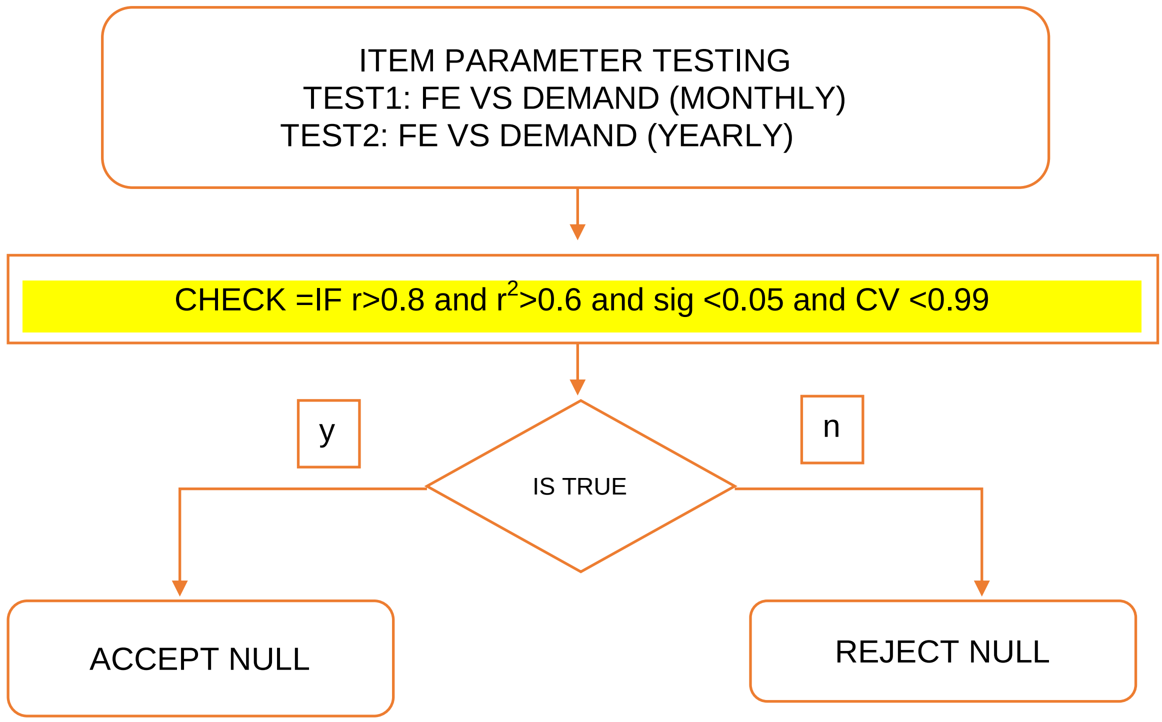
For the purpose of this research, the flying effort data (The independent variable) for the past 60 months have been accessed from IMMOLS. The actual flying effort is recorded in a flight data book (Form 700). This data is entered in

IMMOLS on monthly granularity basis through a graphic user interface form dully approved by the assigned authorities.

3.9 Correlation Analysis.

Bivariate Correlation analysis was undertaken to check the strength and nature of relationship between Flying Effort and Monthly Demand as well as for yearly demand. In addition, the variability of the item demands was also measured by computing the CV values. The data extracted from IMMOLS and SPSS was inserted into MS EXCEL worksheets and an automated program for hypothesis testing was developed using the following logic: -

Figure 3.3 Hypothesis Testing Logic



3.10 Conclusion

The research involved analyzing and accessing authentic ERP data of IMMOLS and testing the casual relationship between flying effort and consumption of spares. The design and flow of the research involved extraction of sample (critical ARS and Non-ARS data) and subjecting them to correlation analysis and testing the null hypothesis as the first construct. In the second construct the research involved comparison of the forecasting accuracy of the existing model with contemporary models such as SES, Holt, Croston etc.

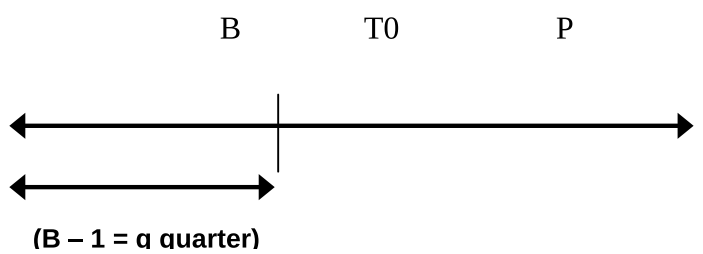
CHAPTER: 4 ANALYSIS AND DISCUSSIONS

4.1 Introduction

In this chapter an analysis of the forecasting algorithm of IAF and the test of correlation between Flying Effort and Demand has been undertaken. Subsequently a forecasting model comparison has been undertaken by using and Excel based forecast modeller.

4.2 For ease of understanding we shall use the following convention for deriving the Algorithms: -

Forecasting Review



T0	=	Forecasting Review Instant
B	=	Base Period
P		Forecast Period
DB	=	Demand during Base period for q quarters

(q = B-1)

o

$= \Sigma$ D q

q = - (B – 1)

F_B = Flying hours achieved during base period (Program data)

$$= \sum_{q = -(B-1)}^{o} F_q$$

AD_P = Forecast demand estimate for P period

$$= \sum_{q=1}^{o} D_q$$

AF_P = Forecast flying effort for P period (Forward Ordering Period)

$$= \sum_{q=1}^{o} F_q$$

4.3 Derivation of Straight Run Method (Non-Airborne).

The straight run method assumes average demand is constant. In such a cast the forecasting algorithm is:-

D_P (Forecast Demand estimate) $= \frac{P}{B} \times D_B$

Eg. If D_B = 100 for last 12 months (CAR) P = 60 Months

B = 12 Months

$$D_P = \left\{\frac{60}{12}\right\} X \quad 100 \quad = \quad 500$$

This formula has been adopted in IAF for Non – airborne spares.

4.4 Derivation of Program Method for Airborne Spares.

This method assumes average demand is proportional to total flying hours. It is essentially a moving average corrected by a Program Factor (Forecast Factor). The forecasting algorithm is:

$$D_P = D_B \quad X \left\{\frac{F_P}{F_B}\right\}$$

D_P (Forecast Demand during MPE Period) = {Current Annual Rate of consumption (CAR)} X (Forecast Factor)

4.5 Derivation of Weighted Moving Average Technique Corrected by Program Factor (IMMOLS adopted formula).

In this method demand rate is weighted by flying hours in order to smoother spikes or sudden surges in consumption pattern. The algorithm is: -

$$D_P = D_B \quad X \left\{\frac{F_P}{F_B}\right\}$$

Where,

$$D_B = \frac{D_1F_1 + D_2F_2 + D_3F_3 + \ldots\ldots\ldots + D_XF_X}{F_1+F_2+F_3+\ldots\ldots\ldots\ldots F_X}$$

$$= \frac{\Sigma\, D_qF_q}{\Sigma\, F_q}$$

$$D_P = \frac{\Sigma\, D_qF_q}{\Sigma\, F_q} \text{ X } \left\{\frac{F_P}{F_B}\right\}$$

This is the basis of the formula used in the IMMOLS application software.

$$(\text{CAR})\ D_B = \frac{(C_1FE_1) + (C_2FE_2) + \ldots\ldots\ldots\ldots + (C_nFE_n)}{FE_1+FE_2\ldots\ldots\ldots\ldots + FE_n}$$

$$= \frac{\Sigma\ C_nFE_n}{\Sigma\ FE_n}$$

Gross Requirement $D_P = \text{CAR x FF}$

$$= \frac{\Sigma\ C_nFE_n}{\Sigma\ FE_n} \text{ X } \frac{F_P}{F_B}$$

4.6 Test for Construct 1: Test of Correlation between Flying Effort and Demand

4.6.1 Analysis of ARS Data (Appendix A&B)

The ARS Sample of 100 items exhibited the following statistical patterns:

Table 4.1 Correlation Analysis

	RANGE					
	STRONG		MODERATE		WEAK	
	LINEAR	INVERSE	LINEAR	INVERSE	LINEAR	INVERSE
PEARSON'S CORRELATION	**1**	**0**	**0**	**0**	**40**	**59**
SIGNIFICANCE	**Correlated with LoS < 0.05**		**Correlated with LoS < 0.01**		**No correlation> 0.05**	
	2		**0**		**98**	

HO	FLYING EFFORT AND CONSUMPTION ARE CORRELATED			
IF	r >0.5 & Sig <0.05 or 0.01		POSITIVE CORRELATION	NULL HYPOTHESIS IS ACCEPTED
IF	r <0.5 & Sig >0.05 or 0.01		NEGATIVE CORRELATION	NULL HYPOTHESIS IS REJECTED
N	100			

4.6.2 Strength of Relationship

Contrary to expectations, weak correlation exists between flying effort and demand of ARS items for 99% items for monthly granularity.

4.6.3 Nature of Relationship.

Contrary to expectations, only a very insignificant % variability of demand can be attributed to variability in flying effort. There may be other reasons which cause this variability and the same can be ascertained through further research.

4.6.4 Testing of Hypothesis for ARS Items

Table 4.2 Results of testing of ARS

HYPOTHESIS TESTING	MONTHLY DATA			
	NO	%		
ACCEPT	0	0		
REJECT	99	99%		

INFERENCES	In case data is aggregated monthly, the data parameters did not pass the logic defined in 99 % of cases. **Hence Null hypothesis in case of ARS items is rejected due to significant high level of rejections. This indicates that the current forecasting algorithm for consumable items used in IMMOLS needs a relook.**

4.6.5 Analysis of Non-ARS Data (Appendix D&E)

The statistical analysis of Non-ARS items using tools of SPSS and MS Excel was undertaken. The details are placed at **Appendix D & E**. The Non- ARS Sample of 100 items exhibited the following statistical patterns:

Table 4.3 Correlation Analysis

	RANGE					
	STRONG		MODERATE		WEAK	
	LINEAR	INVERSE	LINEAR	INVERSE	LINEAR	INVERSE
PEARSON'S CORRELATION	**1**	**0**	**1**	**0**	**51**	**47**
SIGNIFICANCE	**Correlated with LoS < 0.05**		**Correlated with LoS < 0.01**		**No correlation> 0.05**	
	2		**0**		**98**	

H0	FLYING EFFORT AND CONSUMPTION ARE CORRELATED									
IF	r >0.5 & Sig <0.05 or 0.01		POSITIVE CORRELATION		NULL HYPOTHESIS IS ACCEPTED					
IF	r <0.5 & Sig >0.05 or 0.01		NEGATIVE CORRELATION		NULL HYPOTHESIS IS REJECTED					
N	100									

4.6.6 Strength of Relationship.

Contrary to expectations, weak correlation exists between flying effort and demand of ARS items for 98% items for monthly granularity.

4.6.7 Nature of Relationship

Contrary to expectations, only a very insignificant % variability of demand can be attributed to variability in flying effort. There may be other reasons which cause this variability and the same can be ascertained through further research.

4.6.8 Testing of Hypothesis for Non ARS Items

Table 4.4 Results of testing for Non ARS

HYPOTHESIS TESTING	MONTHLY DATA			
	NO	%		
ACCEPT	0	0		
REJECT	98	98 %		
INFERENCES	In case data is aggregated monthly, the data parameters did not pass the logic defined in 99 % of cases. **Hence Null hypothesis in case of Non ARS items is rejected due to significant high level of rejections. This indicates that the current forecasting algorithm for consumable items used in IMMOLS needs a relook.**			

4.6.9 Validation of Hypothesis for Construct 1: Results

Results Considering the details deliberated above, the following can be inferred: -

- Sufficient statistical evidence is available to **reject the Null hypothesis**.
- There exists **very low correlation between Flying Effort and demand rate of consumable items.**

- Very **insignificant percentage of variability of demand** can be attributed to variability in flying effort.

- While Demand pattern ARS items show Normal distribution, the Non-ARS items exhibit **Poisson and Erratic distribution** pattern thereby indicating a **need for application of different forecast models**, instead of the existing Program method, for achieving better accuracy. **Accordingly, samples of 10 critical ARS items and 10 Non- ARS items, have** been specifically chosen to undertake **Forecast Modeling Test** in the next segment.

4.7 Test for Construct 2: Forecasting Model Comparison

. For the purpose of Testing of Hypothesis for construct 2 involving comparison of forecasting accuracy of current model vis a vis other models, a sample of 10 ARS and 10 Non-ARS Critical items have been selected. For ease of comparison, **an Online Forecast Modeler has been designed** based on MS EXCEL that helps in finding out the best suited forecasting model for the items under test.

4.7.1 Software Architecture

The Screen Print of the Front End of the Forecast Modeller is shown below: -

Figure 4.1 Forecast Modeller

FORECAST MODELER

I_CODI	NULL_HYP_YR	DIST_NAM	HYP_FIN	MASE_NAIV	MASE_TOT_AV	MASE_SES1	MASE_SES2	MASE_HOLT	MASE_CROSTON	BEST_FIT
1323	FALSE	ERRATIC	FALSE	1.13783	0.92784	0.95783	0.98938	1.03331	0.63744	CROSTON
3877	FALSE	POISSON	FALSE	1.00000	0.80050	0.95747	0.79731	1.10531	0.72646	CROSTON
4385	FALSE	POISSON	FALSE	1.00000	0.93397	1.13672	0.86156	1.35894	1.25258	SES2
7171	FALSE	ERRATIC	FALSE	1.00000	0.61746	0.89125	0.71662	1.11011	0.63945	TOTAVG
8373	FALSE	POISSON	FALSE	1.00000	0.79926	1.06124	0.84571	1.10259	0.83032	TOTAVG
8697	FALSE	POISSON	FALSE	1.00000	0.73677	0.70822	0.80337	0.80218	0.70552	CROSTON
18085	FALSE	POISSON	FALSE	1.00000	0.84965	0.82410	0.82410	0.83180	0.79421	CROSTON
18090	FALSE	POISSON	FALSE	1.00000	0.78695	0.76298	0.75785	0.77738	0.75586	CROSTON
18711	FALSE	POISSON	FALSE	1.00000	0.62785	1.28176	0.72516	1.84133	0.58426	CROSTON
227905	FALSE	ERRATIC	FALSE	1.00000	0.67363	0.81314	0.78719	0.78923	0.55407	CROSTON

The software was programmed to undertake the following tasks: -

- It picks up the monthly demand data of past 100 months of the 20 selected sample items.
- It then calculated the Minimum Absolute Scaled Error (MASE) in case the data is subjected to the following six standard forecasting models: -

Table 4.5 Forecasting Models

SLNO	MODEL	PROGRAM LOGIC IN ONLINE FORECAST MODELER
1	**IMMOLS _CAR_FE** (SIMULATING THE CURRENT DATA MODEL IN USE IN IAF)	$\frac{\Sigma\ C_nFE_n}{\Sigma\ FE_n}$ ERROR= DEMAND(To) – DEMAND($T_{1)}$ SCALED ERROR = ERROR / MAE ABS = I ERROR I MASE = AVERAGE (ABS ERROR)
2	**TOTAL AVERAGE**	TOTAL AVERAGE = INCREMENTAL AVG ERROR= DEMAND(To) – TOTAL AVG($T_{1)}$ SCALED ERROR = ERROR / MAE ABS = I ERROR I MASE = AVERAGE (ABS ERROR)
3	**STANDARD EXPONENTIAL SMOOTHING (SES1)** WITH OPTIMIZED SMOOTHING PARAMETER OF 0.05	SES = X*D_1+ (1-X)*$SES_{1\ ;\ X=0.05}$ ERROR= DEMAND(T1) – TOTAL AVG($T_{1)}$ SCALED ERROR = ERROR / MAE ABS = I ERROR I MASE = AVERAGE (ABS ERROR)
4	**STANDARD EXPONENTIAL SMOOTHING (SES2)** WITH OPTIMIZED SMOOTHING PARAMETER OF 0.01	SES = X*D_1+ (1-X)*$SES_{1\ ;\ X=0.01}$ ERROR= DEMAND(T1) – TOTAL AVG($T_{1)}$ SCALED ERROR = ERROR / MAE ABS = I ERROR I MASE = AVERAGE (ABS ERROR)
5	**HOLT** WITH ALPHA & BETA SMOOTHING PARAMETER	ALPHA SERIES= α*d1+ (1-α)*(αS+βS) BETA SERIES = β*D1+ (1-α)*(αS+βS) ERROR= DEMAND(T1) – SUM (αS+βS) SCALED ERROR = ERROR / MAE ABS = I ERROR I MASE = AVERAGE (ABS ERROR)
6	**CROSTON**	Actual Demand Forecast Demand = D_1 * Smoothing parameter (0.01) Actual Intervals = =IF(AM5>0, AI1*AM5+(1-AI1) *AN5, AN5) FORECASTS= FORECAST SIZES / FORECAST INTERVALS ERROR= DEMAND(T1) – Forecasts SCALED ERROR = ERROR / MAE ABS = I ERROR I MASE = AVERAGE (ABS ERROR)

4.7.2 For computing the **Best Fit model** with minimum forecast error, the software has been programmed with the following logic: -

= IF(U3=MIN (U3:Z3),"CAR_FE",
IF (W3=MIN (U3:Z3),"SES1",
IF (X3=MIN (U3:Z3),"SES2",
IF (Y3=MIN (U3:Z3),"HOLT",
IF (Z3=MIN (U3:Z3),"CROSTON",
IF (V3=MIN (U3:Z3),"TOT AVG"
)))))

4.7.3 Forecasting Model Comparison Data Output.

The sample data output of 10 critical items from the **online forecast modeller** is as follows: -

Table 4.6 Online Forecast Modeller

ITEMCODE	MASE _CAR	MASE_TOT_AVG	MASE_SES1	MASE_SES2	MASE_HOLT	MASE-CROSTON	BEST FIT
V 161	0.58	0.21	0.5	0.2	0.57	0.53	SES2
V 186	0.61	0.52	0.51	0.33	0.59	1.48	SES2
V 296	0.62	0.91	0.98	0.83	0.85	0.74	CAR_FE
V 388	0.9	0.65	0.61	0.6	0.63	0.65	SES2
V 389	0.65	0.4	0.41	0.39	0.46	0.57	SES2
V 398	1.11	0.64	0.98	0.64	1.18	0.99	SES2
V 406	0.7	0.24	0.57	0.23	0.77	0.59	SES2
V 450	0.92	0.91	1.03	0.96	0.99	0.86	CROSTON
V 451	1.37	1.28	1.46	1.39	1.37	1.31	TOT AVG
V 462	0.5	0.6	0.66	0.52	0.46	0.53	HOLT

Inferences. The results show that t**he current forecasting model (IMMOLS_CAR_FE) has significantly higher Minimum Absolute Standard Error (MASE) values in all cases. In each case the forecast modeler has provided the best forecasting model based on minimum MASE values**

4.7.4 Validation of Hypothesis for Construct 2: Results

Results Considering the details deliberated above, the following can be inferred: -

- The current forecasting model (IMMOLS_CAR_FE) has significantly higher Minimum Absolute Standard Error (MASE) values relative to the other 5 models. **Hence, we may say that sufficient statistical evidence is available to reject the Null hypothesis.**

- **Superior forecasting models may be incorporated in IMMOLS for getting better forecasting accuracy based on the distribution patterns of the item demands.**

4.8 Conclusion

The research clearly indicates rejection of the NULL Hypothesis. It clearly proves that there lies weak correlation between flying effort and consumption and therefore, there is a need to adopt a superior forecasting model. Towards the same a forecast modeller has been designed which checks the demand distribution pattern and provides the best forecasting model for each item based on minimum forecasting error. It would be prudent for IAF to shift over from the existing archaic model to the new strategy and automate the same in IMMOLS.

CHAPTER: 5 SUMMARY AND RECOMMENDATIONS

5.1 Introduction

5.1.1 The current forecasting system adopted by IAF for consumable spares is modelled on Causal Forecasting Models (Cause effect relationship between flying effort and demand). Review done on this reveals the fact that such models work well only for smooth and continuous demand and not when the pattern is intermittent and erratic. This model has many inherent inconsistencies as future consumption does not always follow the past trends and is affected by many variable factors such as environment, the stresses and strains under which aircraft are operated and the technical practices and modifications. It is extremely difficult to measure the relationship of these secondary factors with demand variability and hence it may be prudent to migrate from the existing Linear regression type of a Explanatory / Causal model to either a multiple regression method or to advanced time series and smoothing techniques which predominently adopts a black box approach by giving no relevance to factors.

5.1.2 Keeping the above logic in mind the research hypothesis was formulated and tested: -

- H_o - Null Hypothesis. The Null hypothesis was "The traditional model of forecasting of consumable spares used in IMMOLS based on program factors provides the desired level of forecasting accuracy." The two constructs measured were:
    - Evaluating the IMMOLS forecasting model based on program factors by determining the strength and nature

of relationship between Flying Effort and demand of consumable spares.

- Comparative study and evaluation of current forecasting model with modern prediction techniques.

- H_a - Alternate Hypothesis If the traditional model for forecasting of consumable spares based on program factors is replaced with modern prediction technique(s) then the service level of these ranges of spares would show a quantifiable improvement.

5.2 Test of Correlation between Flying Effort and Demand

Bivariate Correlation analysis was undertaken to check the strength and nature of relationship between Flying Effort and Monthly Demand as well as for yearly demand. In addition, the variability of the item demands was also measured by computing the CV values. The data extracted from IMMOLS and SPSS was inserted into MS EXCEL worksheets and an automated program for hypothesis testing was developed.

5.3 Results

The summary of results is highlighted below: -

5.3.1 ARS Items

In case data is aggregated monthly, the data parameters did not pass the logic defined in 99 % of cases.

Hence Null hypothesis in case of ARS items is rejected due to significant high level of rejections. This indicates that the current forecasting algorithm for consumable items used in IMMOLS needs a relook.

5.3.2 Non-ARS items

In case data is aggregated monthly, the data parameters did not pass the logic defined in 99 % of cases.

Hence Null hypothesis in case of Non ARS items is rejected due to significant high level of rejections. This indicates that the current forecasting algorithm for consumable items used in IMMOLS needs a relook.

5.4 Validation of Hypothesis for Construct 1.

Considering the details deliberated above, the following can be inferred: -

- Sufficient statistical evidence is available to **reject the Null hypothesis**.
- There exists **very low correlation between Flying Effort and demand rate of consumable items.**
- Very **insignificant percentage of variability of demand** can be attributed to variability in flying effort.
- While Demand pattern ARS items show Normal distribution, the Non-ARS items exhibit **Poisson and Erratic distribution** pattern thereby indicating a **need for application of different forecast models**, instead of the existing Program method, for achieving better accuracy.

5.5 Test for Construct 2: Forecasting Model Comparison

5.5.1 For the purpose of testing of Hypothesis for construct 2 involving comparison of forecasting accuracy of current IMMOLS-CAR_FE model vis a vis other models, a sample of 10 ARS and 10 Non-ARS Critical items was selected. For ease of comparison **an Online Forecast Modeler** based on MS EXCEL has been designed that helps in finding out the best suited forecasting model for the items under test. Keeping the limitations of time and data availability the online forecast modeler was used only for comparing standard Smoothing / Time Series and Exploratory models with the Program method.

5.5.2 Results

Inferences The results using SPSS and Forecast modeller show that t**he current forecasting model (IMMOLS_CAR_FE) has significantly higher Minimum Absolute Standard Error (MASE) values in all cases. In each case the forecast modeler has provided the best forecasting model based on minimum MASE values.**

Table 5.1 Online Forecast Modeller

ITEMCODE	MASE _CAR	MASE_TOT_AVG	MASE_SES1	MASE_SES2	MASE_HOLT	MASE-CROSTON	BEST FIT
V 161	0.58	0.21	0.5	0.2	0.57	0.53	SES2
V 186	0.61	0.52	0.51	0.33	0.59	1.48	SES2
V 296	0.62	0.91	0.98	0.83	0.85	0.74	CAR_FE
V 388	0.9	0.65	0.61	0.6	0.63	0.65	SES2
V 389	0.65	0.4	0.41	0.39	0.46	0.57	SES2
V 398	1.11	0.64	0.98	0.64	1.18	0.99	SES2
V 406	0.7	0.24	0.57	0.23	0.77	0.59	SES2
V 450	0.92	0.91	1.03	0.96	0.99	0.86	CROSTON
V 451	1.37	1.28	1.46	1.39	1.37	1.31	TOT AVG
V 462	0.5	0.6	0.66	0.52	0.46	0.53	HOLT

5.5.3 Validation of Hypothesis for Construct 2.

Considering the details deliberated above, the following can be inferred: -

- The current forecasting model (IMMOLS_CAR_FE) has significantly higher Minimum Absolute Standard Error (MASE) values relative to the other 5 models. **Hence, we may say that sufficient statistical evidence is available to reject the Null hypothesis.**
- **Superior forecasting models may be incorporated in IMMOLS for getting better forecasting accuracy based on the distribution patterns of the item demands.**

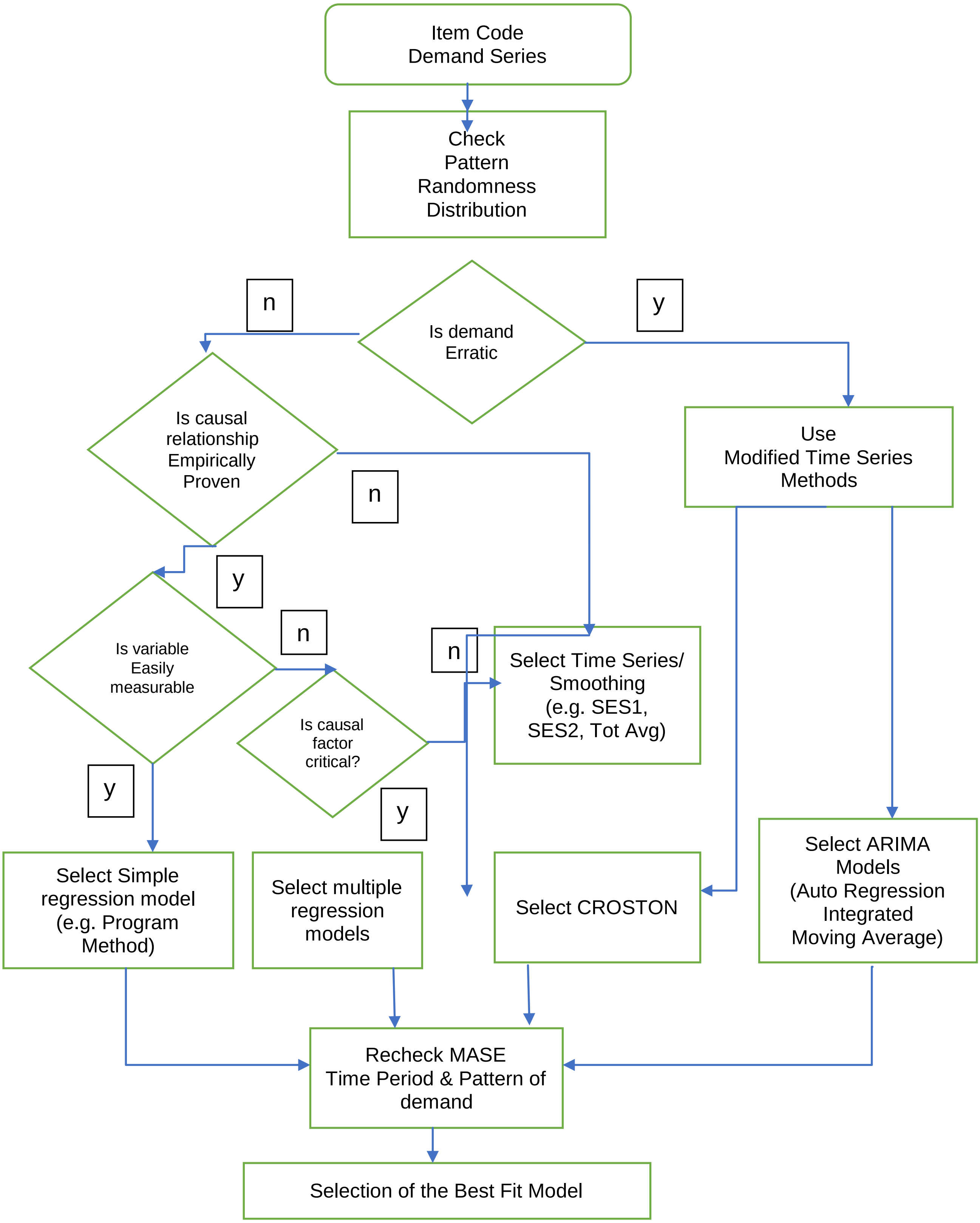
5.6 Recommendations

5.6.1 This research has clearly brought to light the need for shifting from the archaic Program method to a more scientific and modern forecasting technique that would increase forecasting efficacy for consumable aviation spares.

5.6.2 Considering the need to have a flexible approach based on distribution of data, it is therefore recommended that an **Online Forecast Modeler** be **dovetailed in the IMMOLS Provisioning module based on the algorithm suggested in this dissertation**. This would help in availability of a simple user friendly forecast assistance interface which can be easily used by the Fleet managers without getting into intricacies of complex statistical algorithms as the challenge is to predict what will happen and not why it happened.

5.6.3 The Modeler will extract demand data and suggest the best suited model to the fleet manager. The fleet manager would have the discretion to use the same or override it or combine it with his judgmental forecast, wherever required.

Figure 5.1 Flow Chart for Selecting Best Forecasting Model

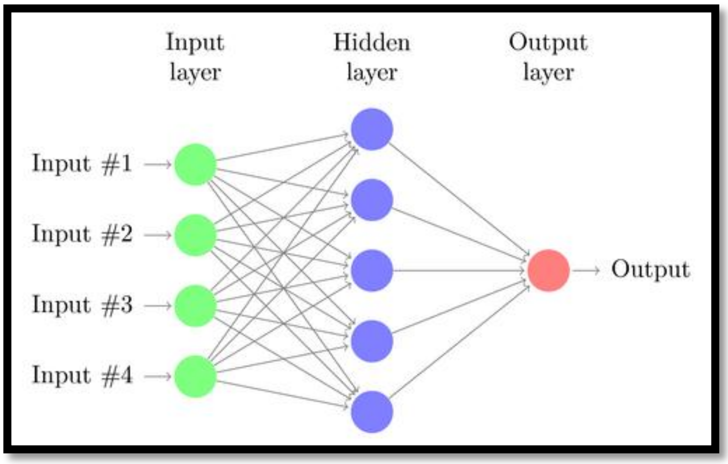


5.7 Scope for Further Research/Study

5.7.1 Extending the Scope Due to paucity of time and lack of access to all data resources of IMMOLS, this research could be conducted only for consumable spares of Akashdeep aircraft. However there is an immediate need to extrapolate this research to all types of spares (including **Rotables, Repairables & TTGE**) for **all the fleets of IAF with different demand aggregation time periods**. This will help understanding the complexities holistically and adapt suitable forecasting techniques keeping such complexities in mind. Such research should include comparison with **ARIMA based models** also as the same could not be undertaken due to lack of adequate data specific to the requirement of the model.

5.7.2 Application of Neural Networks to Time Series Forecasting There is also an immediate need to undertake research in development of prediction models using **Artificial Neural Networks.** This fall in the zone of **Big Data** and will entail usage of multilayered feed forward neural network. Such systems would help in automatic learning of dependencies only from measured data without need to add further information. The neural network would undertake data mining from the history table in order to **discover hidden dependencies** and use the same for future predictions.

Figure 5.2 Artificial Neural Networks



5.8 Conclusion

In this study the readers have been taken though a whirlwind tour of Forecasting management practices and evaluation of existing Forecasting models of IAF, specific to consumable items. At the end, it is presumed that this research will prod serious readers to take a relook at our archaic provisioning philosophies. A road map for a paradigm shift in Provisioning in IAF purely based on mathematical and scientific presumptions has been attempted. However, the subject of provisioning is vast and it has not been possible to deliberate all the contentious issues that plague us, due to inherent limitations of the framework of our dissertations. Notwithstanding the same, the policy planners are urged to consider this research work a trigger for constituting a high-level committee for revision of Provisioning philosophy in the Indian Air Force.

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Appendix A

PROGRAMME OUTPUT FOR FE VS ARS DEMAND (MONTHLY GRANULARITY)

ITEM	r	R^2	SIG_	MEAN	SD_	VAR	CV	NULL HYP
2102	-0.02	0.00	0.83	43.50	209.41	9109.51	4.81	FALSE
2153	0.29	0.08	0.00	310.95	249.61	77616.23	0.80	FALSE
2185	0.01	0.00	0.89	275.36	219.49	60437.94	0.80	FALSE
2186	0.29	0.09	0.00	173.84	223.71	38889.22	1.29	FALSE
6882	0.15	0.02	0.14	116.66	684.34	79834.87	5.87	FALSE
8791	0.05	0.00	0.60	207.43	866.96	179833.10	4.18	FALSE
8798	0.06	0.00	0.54	141.46	870.44	123133.01	6.15	FALSE
9140	0.08	0.01	0.41	139.66	905.04	126397.33	6.48	FALSE
9479	-0.10	0.01	0.34	99.25	942.68	93560.99	9.50	FALSE
10642	-0.04	0.00	0.73	165.56	1054.24	174539.31	6.37	FALSE
10658	0.04	0.00	0.67	136.97	1059.72	145150.40	7.74	FALSE
10664	-0.06	0.00	0.57	230.52	1052.10	242530.78	4.56	FALSE
10672	0.04	0.00	0.71	126.16	1061.73	133948.36	8.42	FALSE
11331	0.12	0.01	0.24	155.72	1123.71	174983.50	7.22	FALSE
11334	-0.01	0.00	0.94	248.56	1115.85	277354.43	4.49	FALSE
11698	0.25	0.06	0.01	199.41	1156.10	230538.50	5.80	FALSE
12321	0.00	0.00	0.99	178.59	1221.05	218066.61	6.84	FALSE
12322	0.05	0.00	0.65	211.80	1219.84	258362.96	5.76	FALSE
12326	0.08	0.01	0.44	180.27	1221.40	220182.50	6.78	FALSE
12335	0.01	0.00	0.96	203.31	1220.85	248211.42	6.00	FALSE
12336	0.18	0.03	0.07	200.67	1221.62	245142.28	6.09	FALSE
12375	0.06	0.00	0.53	158.97	1228.58	195306.57	7.73	FALSE
12379	0.05	0.00	0.61	151.60	1229.13	186335.80	8.11	FALSE
12530	0.15	0.02	0.14	197.31	1240.09	244681.57	6.28	FALSE
12647	-0.03	0.00	0.76	195.94	1251.71	245259.08	6.39	FALSE
12668	0.20	0.04	0.05	294.10	1247.53	366898.57	4.24	FALSE
12670	-0.11	0.01	0.29	176.32	1256.58	221560.01	7.13	FALSE
12962	0.10	0.01	0.30	153.96	1289.36	198509.10	8.37	FALSE
13578	0.15	0.02	0.15	186.35	1346.55	250929.78	7.23	FALSE
13891	0.12	0.01	0.23	157.23	1380.40	217040.45	8.78	FALSE
14944	-0.01	0.00	0.91	203.87	1481.90	302114.55	7.27	FALSE
15691	0.18	0.03	0.07	203.47	1556.67	316735.85	7.65	FALSE
15849	0.22	0.05	0.03	209.28	1572.11	329012.02	7.51	FALSE
15927	0.08	0.01	0.43	213.39	1579.64	337079.38	7.40	FALSE
15964	0.18	0.03	0.08	237.92	1581.47	376263.34	6.65	FALSE

ITEM	r	R^2	SIG_	MEAN	SD_	VAR	CV	NULL HYP
15966	0.20	0.04	0.04	424.75	1567.60	665835.98	3.69	FALSE
15967	0.19	0.04	0.06	337.43	1573.83	531056.44	4.66	FALSE
15968	0.09	0.01	0.39	317.34	1575.93	500105.63	4.97	FALSE
15969	0.13	0.02	0.20	220.42	1583.76	349092.16	7.19	FALSE
15970	0.13	0.02	0.19	289.56	1578.23	456992.28	5.45	FALSE
15971	0.17	0.03	0.10	217.46	1584.11	344480.34	7.28	FALSE
15976	0.18	0.03	0.08	307.21	1576.59	484345.44	5.13	FALSE
15978	0.19	0.03	0.07	296.04	1577.81	467096.06	5.33	FALSE
15980	0.01	0.00	0.90	253.34	1581.31	400608.06	6.24	FALSE
18194	0.22	0.05	0.03	184.81	1809.92	334490.58	9.79	FALSE
18274	0.12	0.01	0.23	235.06	1813.11	426189.40	7.71	FALSE
18946	-0.02	0.00	0.81	187.65	1885.19	353756.09	10.05	FALSE
20106	0.10	0.01	0.35	274.05	1993.73	546382.25	7.28	FALSE
20836	0.02	0.00	0.86	252.14	2245.76	566246.18	8.91	FALSE
26701	0.19	0.04	0.06	300.84	2653.34	798229.30	8.82	FALSE
27390	0.23	0.05	0.02	331.48	2719.49	901457.87	8.20	FALSE
30376	0.04	0.00	0.70	301.46	3022.46	911149.28	10.03	FALSE
227346	0.13	0.02	0.21	2330.42	22614.07	52700271.69	9.70	FALSE
1231699	0.23	0.05	0.03	12320.26	122546.08	1509799567.58	9.95	FALSE

Appendix B

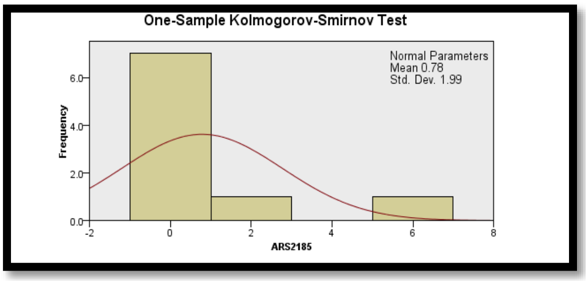
PROGRAMME OUTPUT FOR FE VS ARS DEMAND (YEARLY GRANULARITY)

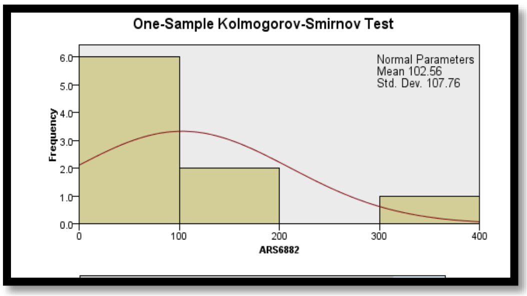
ITEM	r	R^2	SIG_	MEAN	SD_	VAR	CV	NULL HYP
2102	-0.01	0.00	0.98	7.89	5.47	29.87	0.69	FALSE
2153	0.39	0.15	0.31	52.44	43.34	1878.01	0.83	FALSE
2185	0.15	0.02	0.71	0.78	1.99	3.94	2.55	FALSE
2186	-0.15	0.02	0.70	50.11	29.20	852.64	0.58	FALSE
6882	-0.03	0.00	0.95	102.56	107.76	11611.79	1.05	FALSE
8791	0.20	0.04	0.60	254.67	273.42	74760.14	1.07	FALSE
8798	0.91	0.83	0.00	3250.33	833.13	694103.93	0.26	TRUE
9140	0.90	0.82	0.00	2847.33	787.05	619439.83	0.28	TRUE
9479	0.77	0.59	0.02	1708.00	550.83	303411.49	0.32	TRUE
10642	0.10	0.01	0.80	544.56	432.45	187008.68	0.79	FALSE
10658	0.68	0.46	0.05	1351.00	461.18	212690.68	0.34	TRUE
10664	0.70	0.50	0.03	609.89	225.69	50937.33	0.37	TRUE
10672	0.68	0.46	0.04	551.78	259.94	67569.84	0.47	TRUE
11331	0.73	0.53	0.03	675.56	249.70	62351.59	0.37	TRUE
11334	0.30	0.09	0.43	352.89	350.98	123184.15	0.99	FALSE
11698	0.94	0.88	0.00	1402.11	447.92	200629.64	0.32	TRUE
12321	0.19	0.03	0.63	96.67	194.30	37754.04	2.01	FALSE
12322	0.70	0.49	0.04	488.56	230.26	53021.05	0.47	TRUE
12326	0.89	0.78	0.00	1530.11	460.49	212047.36	0.30	TRUE
12335	0.78	0.61	0.01	938.00	274.83	75529.88	0.29	TRUE
12336	0.73	0.53	0.03	635.22	202.09	40838.75	0.32	TRUE
12375	0.81	0.65	0.01	1007.78	370.12	136985.11	0.37	TRUE
12379	0.79	0.63	0.01	653.44	216.74	46977.53	0.33	TRUE
12530	0.70	0.48	0.04	911.00	368.09	135491.72	0.40	TRUE
12647	0.71	0.50	0.03	881.33	426.82	182177.87	0.48	TRUE
12668	0.21	0.04	0.60	409.00	406.04	164866.05	0.99	FALSE
12670	0.21	0.05	0.58	329.67	255.32	65189.83	0.77	FALSE
12962	0.97	0.95	0.00	822.00	246.08	60554.38	0.30	TRUE
13578	0.92	0.84	0.00	793.67	234.39	54937.73	0.30	TRUE
13891	0.82	0.68	0.01	1892.89	655.92	430231.05	0.35	TRUE
14944	0.78	0.61	0.01	570.89	208.85	43618.32	0.37	TRUE
15691	0.37	0.14	0.32	287.56	289.25	83663.25	1.01	FALSE
15849	0.26	0.07	0.51	582.56	349.82	122374.03	0.60	FALSE
15927	0.33	0.11	0.38	221.00	162.74	26483.66	0.74	FALSE
15964	0.41	0.17	0.27	627.44	308.09	94918.22	0.49	FALSE
15966	0.72	0.52	0.03	539.89	203.92	41584.18	0.38	TRUE

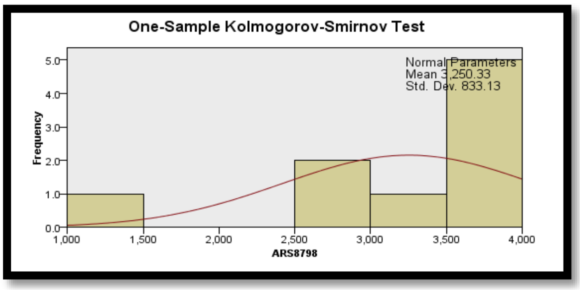
ITEM	r	R^2	SIG_	MEAN	SD_	VAR	CV	NULL HYP
15967	0.76	0.58	0.02	587.56	231.72	53693.23	0.39	TRUE
15968	0.67	0.45	0.05	625.00	221.24	48948.91	0.35	TRUE
15969	0.66	0.44	0.05	896.22	330.50	109232.23	0.37	FALSE
15970	0.82	0.67	0.01	2992.67	828.92	687111.68	0.28	TRUE
15971	0.63	0.40	0.07	2012.56	606.19	367471.17	0.30	FALSE
15976	0.77	0.59	0.02	1787.00	730.35	533403.82	0.41	TRUE
15978	0.39	0.15	0.30	699.22	390.73	152671.50	0.56	FALSE
15980	0.35	0.12	0.36	1475.11	526.31	277000.11	0.36	FALSE
18194	0.78	0.60	0.01	665.78	243.85	59462.33	0.37	TRUE
18274	0.84	0.71	0.00	1672.44	510.75	260865.56	0.31	TRUE
18946	0.86	0.74	0.00	1546.89	477.92	228406.57	0.31	TRUE
20106	0.76	0.58	0.02	1067.44	414.39	171714.93	0.39	TRUE
20836	0.75	0.56	0.02	607.44	217.14	47150.21	0.36	TRUE
26701	0.80	0.63	0.01	841.44	284.26	80803.18	0.34	TRUE
27390	0.18	0.03	0.65	378.67	290.80	84565.80	0.77	FALSE
30376	0.71	0.51	0.03	676.56	259.90	67548.53	0.38	TRUE
227346	0.26	0.07	0.50	891.78	628.13	394543.53	0.70	FALSE
1231699	0.48	0.23	0.20	1280.44	710.76	505172.67	0.56	FALSE

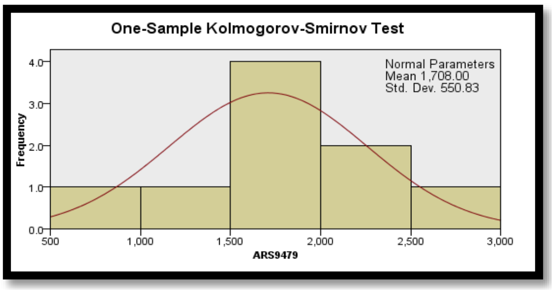
Appendix C

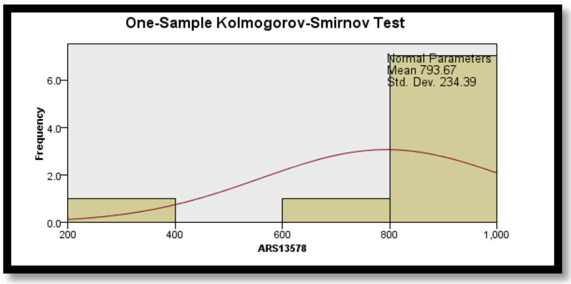
ONE SAMPLE KOLMOGOROV SMIRNOV TEST FOR CRITICAL ARS ITEMS

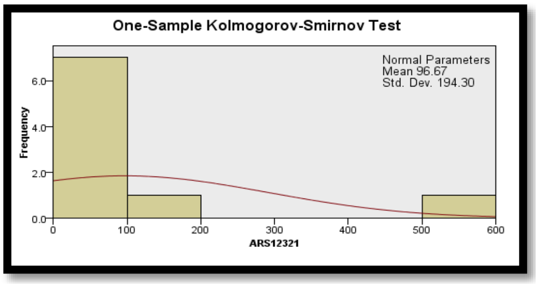


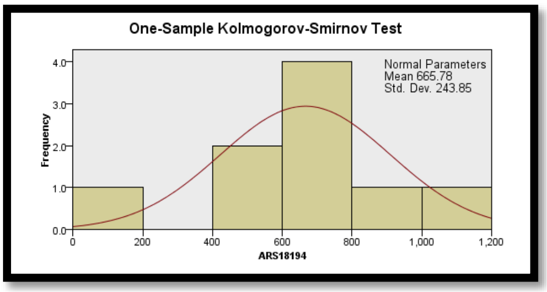


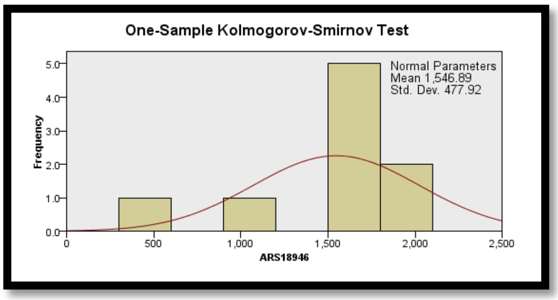


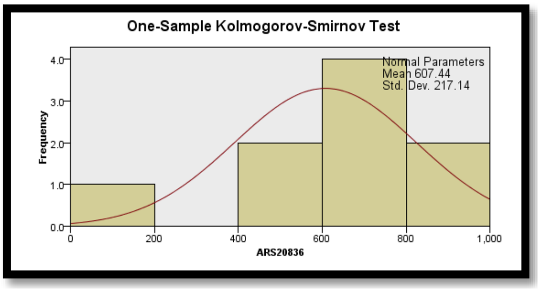


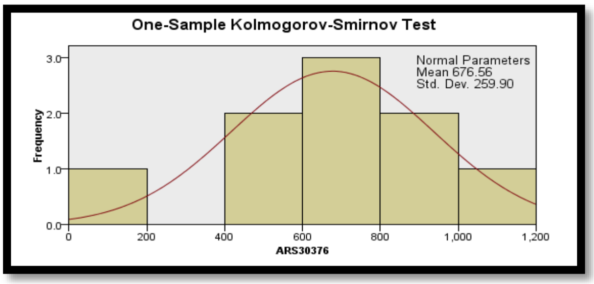












Appendix D

PROGRAMME OUTPUT FOR FE VS NON ARS DEMAND (MONTHLY GRANULARITY)

ITEM	r	R^2	SIG_	MEAN	SD_	VAR	CV	NULL HYP
1323	-0.08	0.01	0.42	7.20	45.53	327.81	6.32	FALSE
2703	0.01	0.00	0.92	8.97	27.72	248.61	3.09	FALSE
3275	0.15	0.02	0.14	1.22	2.98	3.64	2.45	FALSE
3877	0.12	0.01	0.23	0.48	0.69	0.33	1.43	FALSE
3915	0.02	0.00	0.86	3.40	12.79	43.48	3.76	FALSE
3917	0.16	0.02	0.12	5.80	24.79	143.78	4.27	FALSE
4105	0.22	0.05	0.03	61.82	353.26	21838.32	5.71	FALSE
4163	-0.10	0.01	0.35	0.66	2.17	1.43	3.28	FALSE
4385	-0.14	0.02	0.17	0.35	0.59	0.21	1.69	FALSE
4386	-0.29	0.09	0.00	0.35	0.70	0.25	2.00	FALSE
6390	0.10	0.01	0.33	4.02	2.98	11.99	0.74	FALSE
6818	0.13	0.02	0.20	1.01	1.11	1.12	1.09	FALSE
7171	-0.12	0.02	0.22	0.55	1.83	1.01	3.33	FALSE
8373	0.08	0.01	0.46	0.40	0.93	0.37	2.33	FALSE
8697	0.10	0.01	0.33	4.02	2.98	11.99	0.74	FALSE
9989	0.13	0.02	0.20	4.40	17.09	75.20	3.88	FALSE
16529	0.13	0.02	0.18	0.98	6.05	5.93	6.18	FALSE
17307	0.06	0.00	0.56	0.26	0.54	0.14	2.09	FALSE
17585	-0.07	0.00	0.51	4.22	10.78	45.47	2.55	FALSE
17899	-0.05	0.00	0.61	0.32	1.38	0.44	4.30	FALSE
18085	-0.02	0.00	0.85	4.06	2.67	10.85	0.66	FALSE
18090	0.15	0.02	0.14	3.68	2.53	9.33	0.69	FALSE
18436	0.03	0.00	0.77	2.14	13.94	29.84	6.52	FALSE
18711	0.00	0.00	1.00	0.23	1.11	0.26	4.82	FALSE
19253	-0.07	0.01	0.46	6.02	11.91	71.72	1.98	FALSE
20370	-0.06	0.00	0.58	7.69	26.71	205.39	3.47	FALSE
20372	0.20	0.04	0.05	3.43	12.88	44.19	3.76	FALSE
20561	0.21	0.05	0.03	197.15	1056.02	83.3	5.36	FALSE
21144	-0.03	0.00	0.78	38.18	310.66	11860.93	8.14	FALSE
21593	-0.03	0.00	0.80	3.24	21.48	69.60	6.63	FALSE
21613	0.05	0.00	0.59	5.22	18.98	99.10	3.64	FALSE
227905	0.12	0.01	0.24	1.62	5.63	9.13	3.48	FALSE
244647	0.00	0.00	0.99	4478.86	6117.20	63.21	1.37	FALSE
348817	0.01	0.00	0.91	4.42	7.27	32.12	1.64	FALSE
387588	0.02	0.00	0.82	2.49	8.66	21.56	3.48	FALSE
389343	0.01	0.00	0.93	2.55	15.51	39.55	6.08	FALSE

ITEM	r	R^2	SIG_	MEAN	SD_	VAR	CV	NULL HYP
402803	0.05	0.00	0.65	1.93	11.07	21.37	5.74	FALSE
418406	0.16	0.02	0.12	1.16	5.99	6.95	5.16	FALSE
457269	0.07	0.01	0.48	3.62	4.43	16.05	1.22	FALSE
579632	0.10	0.01	0.33	7.17	28.51	204.42	3.98	FALSE
642276	-0.08	0.01	0.42	2.90	11.94	34.63	4.12	FALSE
704822	0.26	0.07	0.01	1.93	1.61	3.11	0.83	FALSE
800868	0.18	0.03	0.07	3.95	16.62	65.64	4.21	FALSE
800986	0.19	0.04	0.06	10.71	13.69	146.60	1.28	FALSE
811035	0.11	0.01	0.26	2.21	2.63	5.81	1.19	FALSE
813314	0.04	0.00	0.71	58.24	71.37	4156.33	1.23	FALSE
895498	0.05	0.00	0.62	7.59	13.48	102.34	1.78	FALSE
895502	0.05	0.00	0.65	3.25	7.11	23.11	2.19	FALSE
895506	0.08	0.01	0.43	4.65	8.94	41.55	1.92	FALSE
895509	0.00	0.00	0.99	5.18	13.53	70.09	2.61	FALSE
895510	-0.11	0.01	0.27	5.62	14.01	78.75	2.49	FALSE
895764	0.28	0.08	0.00	1.90	12.76	24.25	6.72	FALSE
896441	0.10	0.01	0.32	4.31	16.44	70.85	3.81	FALSE
896442	0.03	0.00	0.80	39.64	131.68	5219.71	3.32	FALSE
897651	0.15	0.02	0.14	1.94	6.78	13.15	3.49	FALSE
897672	-0.07	0.00	0.50	5.91	18.72	110.66	3.17	FALSE
897915	0.25	0.06	0.01	0.65	2.38	1.54	3.65	FALSE
900807	-0.14	0.02	0.18	1.10	10.04	11.04	9.13	FALSE

Appendix E

PROGRAMME OUTPUT FOR FE VS NON ARS DEMAND (YEARLY GRANULARITY)

ITEM	r	R^2	SIG_	MEAN	SD_	VAR	CV	NULL HYP
1323	0.04	0.00	0.91	80.00	138.20	19100.00	1.73	FALSE
2703	0.33	0.11	0.38	99.67	86.75	7524.75	0.87	FALSE
3275	0.43	0.18	0.25	9.00	8.08	65.25	0.90	FALSE
3877	0.37	0.13	0.33	5.33	2.92	8.50	0.55	FALSE
3915	-0.95	0.89	0.00	37.78	42.87	1838.19	1.13	FALSE
3917	-0.84	0.70	0.01	64.44	83.08	6902.78	1.29	FALSE
4105	0.23	0.05	0.56	409.11	789.28	3421.76	1.93	FALSE
4163	0.07	0.01	0.86	7.33	6.93	48.00	0.94	FALSE
4385	0.32	0.10	0.40	3.89	2.52	6.36	0.65	FALSE
4386	0.06	0.00	0.88	3.89	3.18	10.11	0.82	FALSE
6390	0.03	0.00	0.94	151.56	220.32	26.35	1.45	FALSE
6818	0.43	0.18	0.25	11.22	3.87	14.94	0.34	FALSE
7171	0.07	0.01	0.86	5.67	8.56	73.25	1.51	FALSE
8373	0.23	0.05	0.55	4.44	3.05	9.28	0.69	FALSE
8697	0.50	0.25	0.17	44.67	18.68	349.00	0.42	FALSE
9989	0.34	0.12	0.37	48.89	60.76	3692.36	1.24	FALSE
16529	-0.09	0.01	0.83	10.89	18.22	332.11	1.67	FALSE
17307	-0.02	0.00	0.96	2.89	1.17	1.36	0.40	FALSE
17585	0.40	0.16	0.29	45.78	35.46	1257.44	0.77	FALSE
17899	-0.25	0.06	0.52	3.56	3.43	11.78	0.97	FALSE
18085	0.66	0.44	0.05	37.00	20.59	424.00	0.56	FALSE
18090	0.54	0.29	0.13	40.89	20.35	414.11	0.50	FALSE
18436	0.08	0.01	0.85	23.78	58.54	3427.44	2.46	FALSE
18711	-0.14	0.02	0.72	2.56	4.42	19.53	1.73	FALSE
19253	-0.28	0.08	0.46	50.44	31.81	1011.78	0.63	FALSE
20370	-0.03	0.00	0.93	85.44	123.57	4321.23	1.45	FALSE
20372	0.33	0.11	0.38	25.33	33.39	1114.75	1.32	FALSE
20561	0.30	0.09	0.44	2190.56	3272.30	2548.11	1.49	FALSE
21144	0.06	0.00	0.89	424.22	1005.76	3412'54	2.37	FALSE
21593	0.29	0.08	0.45	36.00	66.21	4384.00	1.84	FALSE
21613	0.36	0.13	0.34	58.00	63.62	4048.00	1.10	FALSE
227905	-0.47	0.22	0.21	18.00	16.31	266.00	0.91	FALSE
244647	0.50	0.25	0.17	49765.11	53616.42	2631.23	1.08	FALSE
348817	0.41	0.16	0.28	49.44	48.77	2378.53	0.99	FALSE
387588	0.07	0.00	0.87	27.67	29.78	886.75	1.08	FALSE
389343	0.05	0.00	0.91	28.33	52.98	2806.75	1.87	FALSE

ITEM	r	R^2	SIG_	MEAN	SD_	VAR	CV	NULL HYP
402803	0.22	0.05	0.56	21.44	34.06	1159.78	1.59	FALSE
418406	-0.04	0.00	0.93	12.89	16.56	274.11	1.28	FALSE
433202	0.57	0.33	0.11	90.67	58.14	3380.50	0.64	FALSE
457269	0.74	0.55	0.02	96.00	30.66	940.00	0.32	FALSE
579632	0.08	0.01	0.85	79.67	159.15	25329.50	2.00	FALSE
642276	0.41	0.17	0.27	32.22	34.94	1220.69	1.08	FALSE
704822	0.55	0.30	0.13	21.44	9.77	95.53	0.46	FALSE
800868	0.23	0.05	0.54	45.33	66.80	4462.50	1.47	FALSE
800986	-0.09	0.01	0.82	119.00	81.42	6630.00	0.68	FALSE
811035	0.08	0.01	0.85	24.56	19.42	377.28	0.79	FALSE
813314	0.22	0.05	0.57	647.11	521.60	3921.45	0.81	FALSE
895498	0.26	0.07	0.51	84.33	57.47	3302.25	0.68	FALSE
895502	0.11	0.01	0.79	36.11	34.56	1194.36	0.96	FALSE
895506	-0.06	0.00	0.88	51.67	45.62	2081.50	0.88	FALSE
895509	-0.16	0.03	0.68	57.56	44.28	1960.78	0.77	FALSE
895510	-0.09	0.01	0.82	62.44	43.32	1876.78	0.69	FALSE
895764	0.36	0.13	0.34	21.11	42.62	1816.86	2.02	FALSE
896441	-0.05	0.00	0.91	46.78	76.33	5826.44	1.63	FALSE
896442	-0.94	0.88	0.00	262.11	489.52	6543.22	1.87	FALSE
897651	-0.21	0.04	0.59	21.56	21.81	475.53	1.01	FALSE
897672	-0.08	0.01	0.84	63.44	99.63	9925.78	1.57	FALSE
897915	0.40	0.16	0.28	7.22	9.40	88.44	1.30	FALSE
900807	0.05	0.00	0.90	12.22	33.08	1094.44	2.71	FALSE

** **Complete Details data available in data files and will be provided whenever required.**