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Postgraduate Dissertation

“A Comparative Study of Time Series Analysis Models in Demand of Spare Parts for Army Transportation Vehicles”

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Patras, Greece, “June” “2024”

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Abstract

In this dissertation, an attempt is made to analyze monthly demand data for spare parts for military transport vehicles using time series models. Through the systematic analysis of the statistical properties of the demand data, we will initially investigate the presence or absence of significant characteristics of the time series, such as trend and seasonality. Subsequently, we will proceed with the application of various modeling techniques, such as regression analysis, to draw useful conclusions about the monthly demand. The purpose of the research is to determine how predictable the demand is and which model is considered to be more reliable. By using the proposed model, decision-makers for future spare parts orders will contribute to the economic robustness of the organization and the high availability of military transport vehicles.

Keywords

Forecasting demand, spare parts, army vehicles, time series, regression analysis

“Συγκριτική Μελέτη Μοντέλων Ανάλυσης Χρονοσειρών στη Ζήτηση Ανταλλακτικών για Οχήματα Μεταφοράς Στρατού ”

“Ελένη Καραβαγγέλη”

Περίληψη

Στην παρούσα διπλωματική εργασία επιχειρείται η ανάλυση δεδομένων μηνιαίας ζήτησης ανταλλακτικών μεταφορικών μέσων για στρατιωτική χρήση με την εφαρμογή μοντέλων χρονοσειρών. Με τη συστηματική ανάλυση των στατιστικών ιδιοτήτων των δεδομένων ζήτησης θα διερευνηθεί αρχικά η ύπαρξη ή μη σημαντικών χαρακτηριστικών των χρονοσειρών όπως είναι η τάση και η εποχικότητα. Στη συνέχεια, θα προχωρήσουμε στην εφαρμογή διαφόρων τεχνικών μοντελοποίησης όπως είναι η ανάλυση παλινδρόμησης προκειμένου να εξαχθούν χρήσιμα συμπεράσματα για τη μηνιαία ζήτηση. Σκοπός της έρευνας είναι να διαπιστωθεί πόσο προβλέψιμη είναι η ζήτηση και ποιο μοντέλο θεωρείται περισσότερο αξιόπιστο. Με την χρήση του προτεινόμενου μοντέλου οι υπεύθυνοι λήψης απόφασης μελλοντικών παραγγελιών ανταλλακτικών θα συμβάλλουν στην οικονομική ευρωστία του οργανισμού και στην υψηλή διαθεσιμότητα των στρατιωτικών μεταφορικών οχημάτων.

Λέξεις – Κλειδιά

Πρόβλεψη ζήτησης, ανταλλακτικά, στρατιωτικά οχήματα, χρονοσειρές, παλινδρόμηση

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List of Abbreviations & Acronyms

DoD – Department of Defence

DSI – Demand/Supply Integration

GAO - Government Accountability Office

GDP- Gross Domestic Product

IQR - Interquartile Range

MAPE - Mean Absolute Percentage Error

MoD - Ministry of Defence

NATO - North Atlantic Treaty Organization

OIF - Operation Irani Freedom

RAF - Royal Air Force

SCM - Supply Chain Management

SIPRI - Stockholm International Peace Reach Institute

SMA - Simple Moving Average

UK - United Kingdom

1. Introduction

In this thesis, an attempt is made to briefly introduce the basic concepts of demand forecasting, a field that has seen an increased application in various areas in recent years. This trend is largely driven by the rapid advancements in technology and production. The modern environment is characterized by rapid changes, with the most constant element of today's era, the climatic change. Understanding and anticipating the unforeseen consequences of changes in systems such as the supply chain have led to new ways of thinking and acting, with the aim of gaining insight into the potential behavior of systems, such as future demand.

Thus, companies, services, and organizations that operate fleets of vehicles for the transport of personnel and materials seek ways to accurately predict the future demand of spare parts. This allows them to formulate their ordering policies in a manner that ensures vehicle availability will not be affected by external changes, such as war, pandemic environmental and political cricis.

In the military field, supply chain management includes activities related to procurement and maintenance to achieve maximum availability of navy, air force, and army forces. Consequently, the installed logistic systems need to provide all the necessary information about the level of spare parts inventory, avoiding overstocks that increase the cost of supply and storage. Using an accurate forecasting model for the future demand of spare parts is a crucial aspect of decision-making when building the best policies for inventory management.

1.1 Problem Definition

It is well recognized that precise forecasts improve the financial stability of each country, especially in the defence sector. This trend is reinforced by global uncertainties due to wars and the energy crisis. In recent years, companies and organizations, including the military, have experienced either over-insurance or delays in the delivery of spare parts essential for the operational readiness of military vehicles. The issue of lacking critical and common spare parts can be mitigated by implementing a reliable and accurate future demand forecasting model. This approach allows the organisation to maintain procurement and storage costs at acceptable levels, preventing sharp increases, and achieves optimal operational readiness of military forces in an unstable external environment concurrently.

1.2 Purpose

The subject of this thesis is to analyse the monthly demand data for spare parts for army transportation vehicles using an array of time series models. After a systematic and comparative analysis of the statistical properties of the demand records has taken place, the extent to which the proposed modeling techniques provide useful input to the decision-making process will be investigated. The purpose of this study is to identify and suggest the application of an optimal forecasting model for monthly demand in order to increase the operational availability of army transportation vehicles while minimizing the cost of supplying and holding inventory spare parts.

1.3 Methodology

In this research, data of monthly demand pertaining to an army fleet of transport vehicles will be used so as to identify demand patterns, compare different forecasting techniques~~,~~ such as time series analysis~~,~~ suggest an accurate model for the demand of spare parts for military vehicles. Various statistical models, including moving average and regression analysis techniques will be adopted to answer the research questions.

Consequently, the styli~~s~~ed facts of the demand data time series and how likely they are to affect forecasting uncertainty over longer time horizons will be examined. Additionally, another aspect to be examined is how predictable the demand patterns are and research is to be done in which model can be considered to be the most reliable and accurate for the data at hand. Finally, conclusions will be drawn based on the experimental results as well as determining how useful demand forecasts are in the decision-making process for orders and the availability of vehicles.

1.4 Findings

The present research, by using time series techniques, revealed that the demand for spare parts for military transport vehicles has show an upward trend over time. Additionally, the existence of seasonality was confirmed, particularly in June and October. The overall R-Square and MAPE values indicate that the future demand forecasting model is accurate and credible for military agency decision-makers.

1.5 Limitations

The aim of this research is to investigate the existence of patterns in spare parts demand so as to propose a reliable and accurate forecasting model to meet future needs. The sample includes historical demand data over a period of 10 years during peacetime, excluding periods of crisis or war. Additionally, the demand data analysed in this study is considered to be a convenient sample, as it is not categorized into subgroups such as critical or high-value spare parts. Consequently, the cost of supply and storage for these categories is not taken into account in the forecasting model. Finally, the grouping of the four samples of demand for spare parts was based on the mode of movement of the military vehicle and the part of the vehicle where the spare parts are placed. The potential existence of common or interchangeable parts among the four groups is not considered in this study.

1.6 Organization

In this chapter, the general framework of the present research is briefly outlined, the problem and its purpose based on the investigative questions is defined, and the limitations are discussed. Chapter 2 reviews previous case studies related to identifying patterns, trends, and crucial issues in forecasting demand. Chapter 3 describes the theoretical background on which the present research is based. The analysis and outcomes of the present thesis are presented in Chapter 4, while Chapter 5 provides the results and-recommendations are put forward for future research.

2. Literature Review

According to Stockholm International Peace Reach Institute (SIPRI), the two countries with the biggest military spendings in the world are the USA and China with $916 and $296 billion, respectively (SIPRI, 2024). It is obvious that the USA allocate 3,1 times more than the second country and by far is the biggest spender globally. The global military spending as a share of Gross Domestic Product (GDP) has risen from 2,2% to 2,3% in 2023 compared to previous year. The following figure depicts the top 15 countries with the biggest military spending as a share of GDP. The large amount of money the coutries spend on military expenditures reveals the necessity to make accurate forecasting regarding their’s military needs.

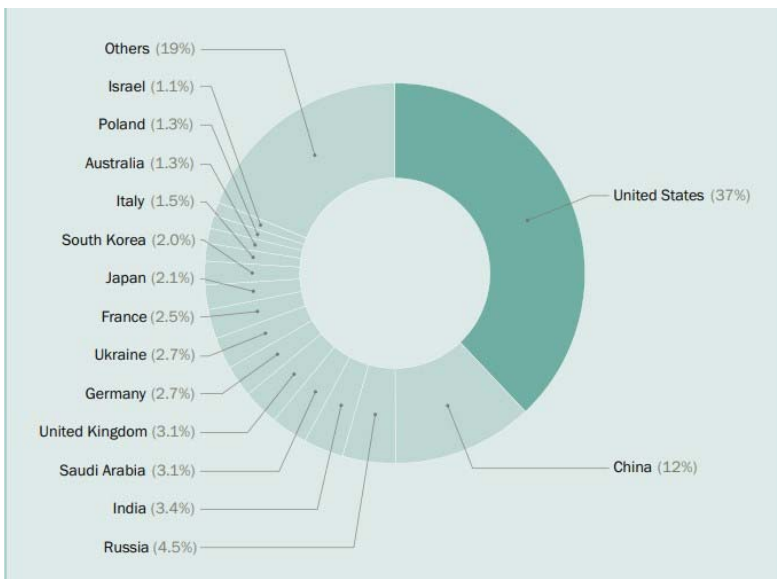

Figure 1 The share of military expenditure of the 15 countries with the highest spending in 2023. (SIPRI, 2024)

Thus, the United States being the greatest military force globally regard the inventory management as one of the most important sectors with high risk. The country invests billions of dollars in military forces in order to supply the combat units «with the right items available at the appropriate time» maintaining them flexible and effective.According to the independent agency, the United States Government Accountability Office, (GAO) and the report to Congressional Committees in April 2005 it was found that the consequences of supply shortages on any army operations are quite difficult to quantify (GAO, 2005). The main reason is the variety from one combat unit to onother even in the same theater of operations. Apart from that, in many cases, the shortages of spare parts especially in critical are not visible to readiness systems of relevant department of the military organization. The GAO studied the Operation Irani Freedom (OIF) and found out that the U.S troops had shortages in seven crucial items such as batteries, tires, and vehicle track shoes. This fact declined the military operational capabilities and at the same time increased the risk posed on troops in theater of military operations.

One characteristic example is that in August 2003, the available inventory of tires for 5-ton transport vehicles was 505 itemsfar away from the global monthly demand which was 4.828 tires. It is worth mentioning that most of them were needed for the military operation in Iraq area. Military operations such as OIF have shown how important is a reliable forecasting method for any crucial requirements for spare and repair parts among others.For this reason, military services use~~s~~ the most suitable computer model to forecast theirs future requirements, taking into account the historical data. In OIF military personnel used the average monthly demand for 2 years combined with submitting operational needs statements for spare parts to analyse and validate the outcomes in order to make accurate adjustments and recommendations (GAO, 2005).

Four years later, in 2009, the GAO examined once again the army data for crucial spare parts such as engines from 2004 to 2007 in order to evaluate and improve the demand forecasts (GAO, 2009). The GAO found out that the military had more inventory for current requirements than it was needed, but at the same time, there were shortages of other items.

On the other side of the Atlantic Ocean, the United Kingdom (UK) is the sixth country in global ranking with the higher military expenditure (SIPRI, 2024). The Royal Air Force (RAF) which is the oldest air force all over the world has one of the largest fleet of Chinook helicopters worldwide.The Ministry of Defence (MoD) in order to enhance the availability of helicopter and the capabilities of RAF tranferred the maintenance to Boeing company. This type of helicopter has 13.000 spare components and some of them are considered to be the most critical in maintenance programme. Thus, the RAF and the company examined the historical orders combined with contract conditions for spare parts by means of an inventory forecasting toolset in order to find out the best maintance policies reducing the duration of each helicopter (Downing, 2011). They concluded among other~~s~~ things, that inaccurate demand data is the reason for failure to align with RAF's requirements.

Okromtchedlishvili (2023) using the application of lenear regression examined the impact of three independent key factors which are considered crucial for military strength and readiness.According to the author, the defence expenditure as a percentage (%) of GDP, the defence expenditure in current prices in US dollars ($) and the military personnel are the independent variables in study. Using data from 31 members countries of North Atlantic Treaty Organization (NATO) the author tried to find out which of the three variables affect more the military capability.The analysis confirms that the military personnel and the defence expenditure are significant in constrast with the defence expenditure as % GDP. Also, the two aforementioned variables affect~~s~~ positively the military power and readiness (Okromtchedlishvili, 2023).

In the industrial sector~~,~~ even a small improvement in spare parts demand forecasting is of great significance because it can result in savings. Despite extensive research~~s~~, forecasting demand remains challenging particularly in military logistics where the demand is irregular. Kim et al. (2023) used data related to spare part demand for a third-generation battle tank in order to suggest the most appropriate forecasting models in military field. The authors applied time series and artificial intelligence techniques and suggested the second as the most accurate method for army spare parts in the defence field (Kim, J. D., Kim, T. H., & Han, S. W, 2023).

Choi and Suh (2020) studied the demand data from spare parts military aircraft from 2015 to 2018 in South Korea. As it is mentioned above, South Korea is the twelfth country with the biggest military spending worldwide. The authors consider that an accurate forecasting is the key to increase the readiness of any weapon system. Using time series analysis in order to forecast the future demand in military field, the aurhors found lower prediction compered to the "random forest" technique. Focusing on four characteristics those of the reliability of spare parts, the information about them, the consumption and the operatiion of an aircraft the nations could strengthen the military forces using their budget in an efficient way (Choi, 2020).

All the aforementioned studies have proven that an accurate demand forecasting model is a crucial factor in controlling and managing the inventory of spare parts to achieve optimal readiness and availability of any weapon system and military forces.

3. Methodology

3.1 Forecasting

Forecasting is a complex activity that can provide a competitive advantage in the global market for companies that excel at it, or for organisations like the army that makes use of it. Successful organisations often have expert teams to ensure accurate forecasts. Different types of data and information are required depending on the sector and the forecast's time horizon. For instance, forecasting future gas demand involves using long-term data, whereas determining the number of employees needed in a call center requires short-term data.

The key factors affecting the predictability of a quantity include the availability of data and the time horizon for making forecasts, which are considered crucial when it comes to effective strategic planning. According to Moon (2018), all forecasts involve uncertainty, and their accuracy diminishes as the time horizon extends. Long-term predictions are particularly risky due to potential changes in political, economic, environmental, and social conditions. Additionally, estimating the availability of materials, labor, transportation capabilities, and machine efficiency could be challenging but essential for a successful and sustainable supply chain (Moon, 2018).

Point forecasts, as defined by scholars, are numerical estimates from predictive models indicating the most likely future value but without information on uncertainty. This limitation makes them less useful for long-term comparisons due to the fact that they are disregarded in terms of variability. On the other hand, interval forecasts offer a range of possible values with a specified confidence level, such as 95%, which indicates the degree of certainty. According to Hyndman and Athanasopoulos (2018), point forecasts carry more uncertainty than prediction intervals. Thus, it is advisable to pair point forecasts with prediction intervals to mitigate uncertainty (Hyndman, 2018).

The balance between supply and demand is considered as a permanent goal for companies and organisations. The following shape illustrates the interaction between demand and supply combined with the financial goals and the strategy of senior leadership in the supply chain generally.

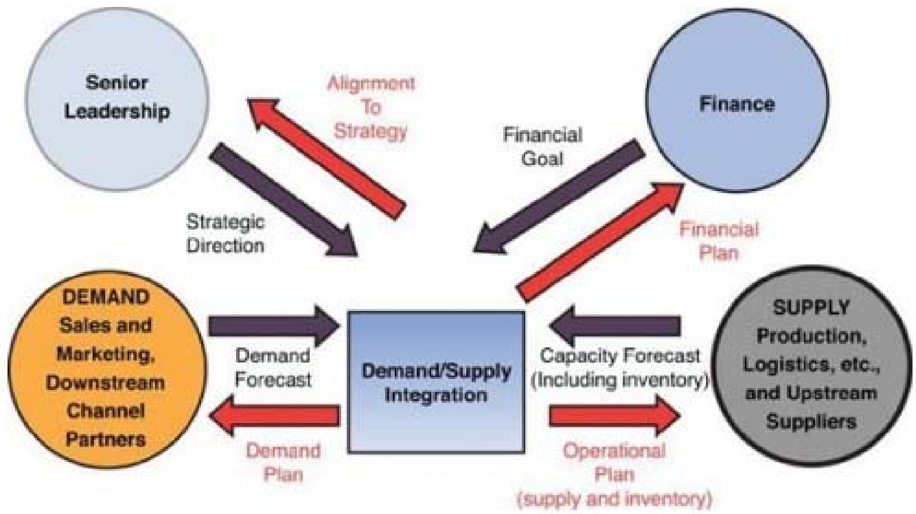

Figure 2 Demand/Supply Integration: the ideal state (Moon, 2018)

The external environment and historical demand data are crucial for any future forecasting to achieve Demand/Supply Integration (DSI) (Esper, 2010). It is obvious how important accurate demand forecasting in supply chain is for a successful company or organisation, such as military forces for nations.

3.2 Forecasting data and methods

As mentioned earlier, the availability of data determines the suitable forecasting method. When data are absent or irrelevant, a qualitative forecasting method is necessary. This method is considered structured and systematic, not merely guess, and can produce reliable forecasts without historical data. On the other hand, quantitative forecasting is applicable when there is numerical historical information to identify future patterns. According to Moon (2018), excellent forecasting is based on three pillars: "statistical forecasts," "qualitative judgments," and the "consensus process." By considering all of these, analysts can accurately predict future patterns.

First of all, it is necessary to define the problem, which is considered to be the most difficult step in the forecasting process. Next, the forecasters gather information, such as historical data, and graph it. At this stage, it is essential to identify if there is a trend, seasonality, and noise in the selected data and how significant each of these components is. Moreover, it is crucial for analysts to choose the appropriate model and determine the strength of the relationship among the selected variables. The final step is to evaluate the results of the selected model to make accurate future forecasts and suggestion (Hyndman, 2018). This procedure will be implemented in the present dissertation.

3.3 Time series analysis

A sequence of observed data over time is known as a time series. Uniform intervals of time include daily, monthly, and annual observations. In this way, the forecaster tries to capture the behavior of any variables over time and to identify patterns and trends to make accurate forecasts. Various tools and techniques are available for time series analysis.

According to researchers, the naïve forecast is the simplest method to predict the value of the next time period. For example, the forecasted value of spare parts demand for February is equal to the actual demand of the previous month. This method does not take into account components such as seasonality or trends in historical demand values.

Another type of forecast is the simple moving average, where the forecast for the next time period is equal to the arithmetic mean of all previous observations of spare parts demand, for example. It is easy to calculate and requires only historical data, making this method suitable for quick estimates. However, the simple average forecast is unable to account for trends, seasonality, recent changes, and outliers, making it unsuitable for complex forecasting needs. This limitation is evident in the following figure, where this method fails to capture the pattern of seasonal demand.

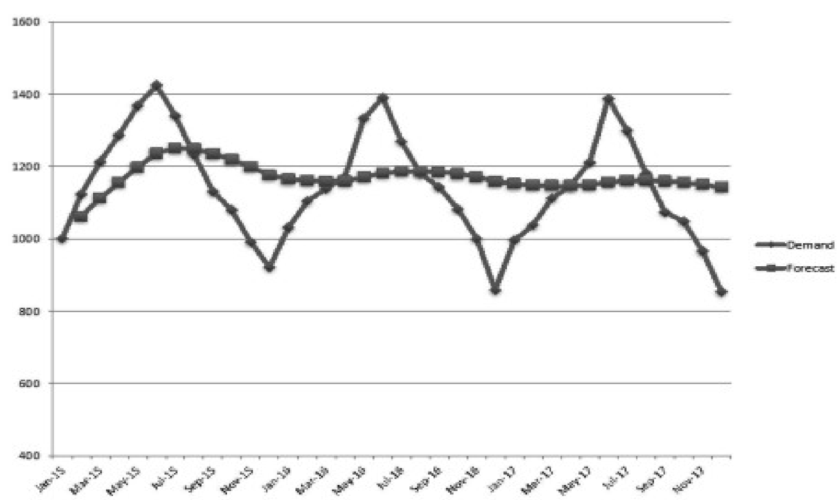

Figure 3 Simple averege method and seasonality (Moon, 2018)

Thus, forecasters use the moving average technique to smooth short-term fluctuations in time series observations and identify longer-term trends or cycles. It is calculated using the following formula.

$F_{t+1} = (D_t + D_{t-1} + D_{t-2} + D_{t-[N-1]})/\ N$ *(equation 3.1)*

$F_{t+1} = Forecast\ for\ next\ period\ t+1$

$D_{t-1} = demand\ for\ period\ t-1$

$N = Number\ of\ periods\ in\ the\ moving\ average$

It is rendered as an easy method to use but less suitable for observations with complex patterns or expected rapid changes. If researchers choose an inappropriate 'window size' (N), the forecasts may be inaccurate, increasing the risk of making wrong decisions. The following figure characteristically illustrates the failure to capture the seasonal demand pattern using three, six, and twelve-month moving averages for future forecasts.

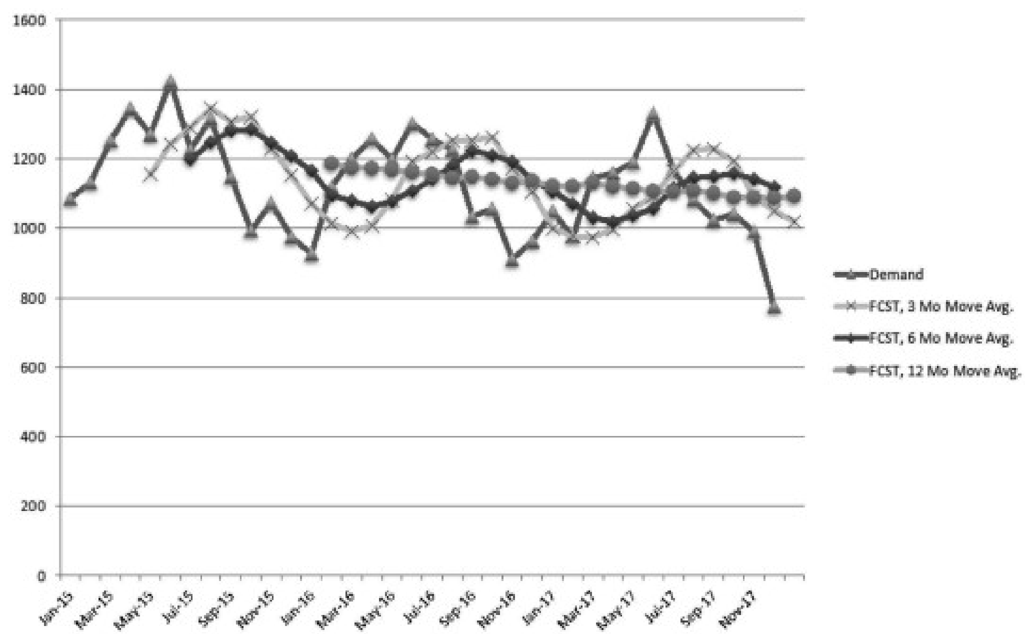

Figure 4 Moving averege method and seasonality (Moon, 2018)

A more flexible time series forecasting method is exponential smoothing. In this technique, the forecaster decides the weight that previous observations will have on future demand. This way, the most recent values have the greatest influence on the forecast. The general formula for calculating exponential smoothing is the following:

$F_{t+1} = \alpha D_t + (1-\alpha)F_t$ *(equation 3.2)*

$F_{t+1} = Forecast\ for\ next\ period\ t+1$

$D_t = Demand\ for\ period\ t$

$F_t = Forecast\ for\ period\ t$

α is the smoothing constant with values $0 < \alpha < 1$

Exponential smoothing is efficient for short-term forecasts and can adapt to changes in observations quickly. It requires very careful selection of the smoothing parameter α to avoid ignoring important fluctuations. Moreover, this method assumes that the data does not have strong seasonality. It is worth mentioning that the method produces inaccurate forecasts for non-stationary observations. The following figure characteristically illustrates the flexibility to choose the suitable value of the constant α to fit the data.

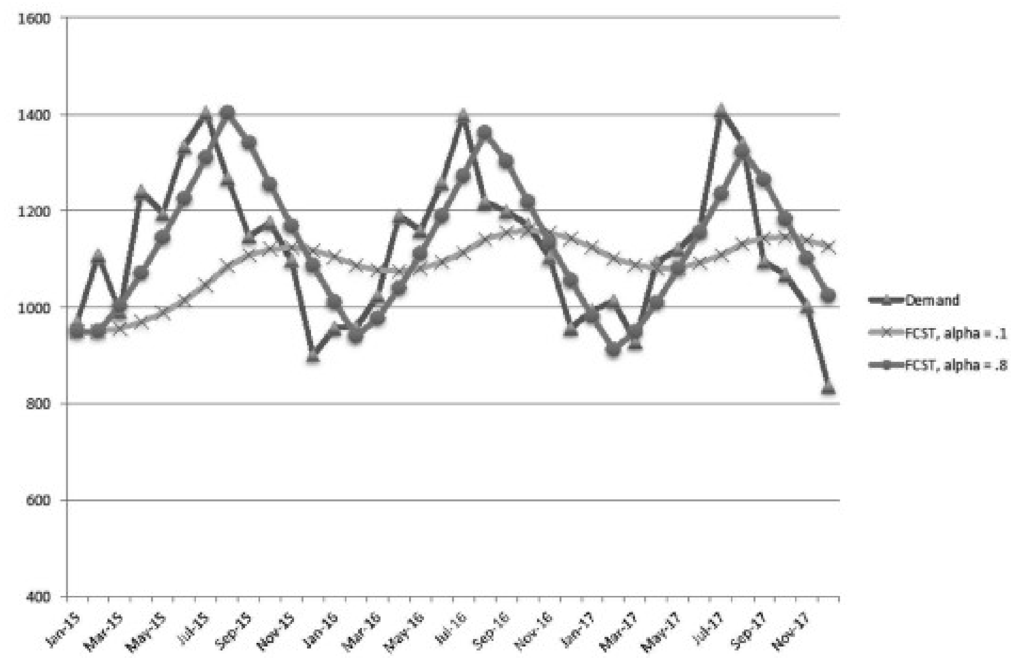

Figure 5 Exponential smoothing and seasonality (Moon, 2018)

3.4 Regression analysis

Regression analysis is a widely used statistical technique employed by forecasters to model and analyze the relationships among variables. The model includes a dependent variable and one or more independent variables. The primary goal is to determine how the dependent variable changes when one of the independent variables varies while the others remain stable. Additionally, it is used to calculate the future value of the dependent variable, such as demand, based on the values of independent variables. In the case of demand, factors influencing it, such as the price of a product, are considered (Moon, 2018).

In time series analysis, a simple linear regression is the most common form and the equation is written as follows:

$Y_t = \beta_0 + \beta_1 X_t + \varepsilon_t$ *(equation 3.3)*

Y_t : *dependent variable for period t*

X_t : independent variable for period t

β_0 : the intercept which represents the value of Y when X is zero

β_1 : the slope which represents the expected change in Y per unit change in X

ε_t : the error term for period t (Hyndman, 2018)

An indicative example of a graphical representation is shown below.

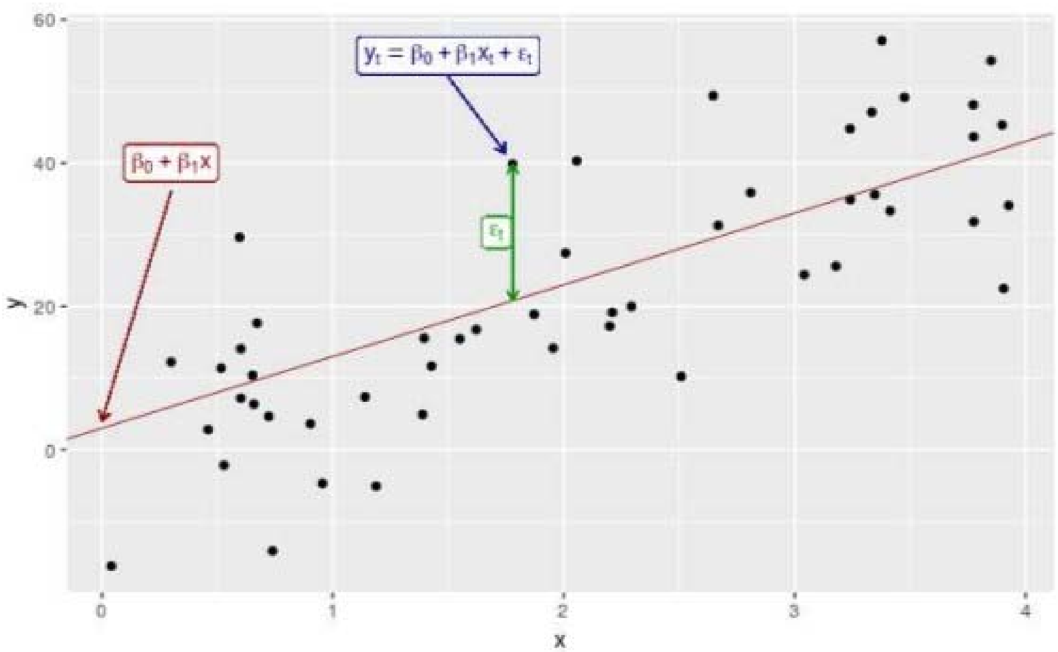

Figure 6 Data from a simple linear regression model (Hyndman, 2018)

The simplicity of this statistical tool makes it applicable in many fields such as the military. Modelling the relationship between variables reserchers make versatile predictions taking into account the most significant factors which influence the outcomes. It is worth mentioning that regression analysis can be affected by outliers and the results are sensitive to the form of the model.It should be stated that regression analysis identify the correlation and many times it is required to study and establish causal links in order to understand complex phenomena (Moon, 2018), (Berenson, 2019).

4. Time Series Analysis and Outcomes

4.1 Case Study- Data

This chapter presents demand data for spare parts of army transportation vehicles for the time period extending from January 2013 to December 2023. The data have been grouped into four categories named "A1", "B1", "A2", and "B2".

Category "A" refers to transport vehicles that move by track shoe, while category "B" uses wheels to move on the ground. Thus, the organisation is able to move its personnel and materials anywhere on the ground which is considered one of its main strategies.

In addition, the two aforementioned categories are further divided into two subcategories. The one labelled with number "1" includes spare parts related to the motion transmission system of the army vehicles, while number "2" includes spare parts relative to the engine's operation.Therefore, the demand data that have been gathered are briefly categorized as follows:

Group A1 refers to transport vehicles moving by track shoe and includes spare parts of the transmission drive system.

Group B1 refers to transport vehicles moving by wheels and includes spare parts of the transmission drive system.

Group A2 refers to transport vehicles moving by track shoe and includes spare parts of the engine system.

Group B2 refers to transport vehicles moving by wheels and includes spare parts of the engine system.

It is evident that the two subcategories of spare parts, the transmission drive system and the engine system~~,~~ are directly linked to the availability of transportation vehicles for use. Failure to meet these needs results in the immobility and non-usage use of the vehicle, thus hindering the organisation's ability to serve transportation needs at any given time.

To sum up, in this case study, data pertaining to the monthly demand for spare parts for military transport vehicles were collected, categorized separately into groups A1, B1, A2, and B2, regarding the period from January 2013 to December 2023. The main goal is to use different forecasting techniques to draw useful conclusions about trends and seasonality of demand and to suggest an accurate forecasting model which decision-makers should take intoconsideration when shaping the future policies of spare parts orders.

4.2 Descriptive Statistics

As mentioned above, there are four groups of data (A1, B1, A2 and B2) spanning over a ten-year period. The demand for spare parts was aggregated into 132 monthly observations from January 2013 to December 2023. The descriptive statistics referring to each group are presented in the following tables.

Table1 Descriptive statistics of monthly spare parts demand for groups A1 and B1 over a time period of 132 months.

GroupA1		*GroupB1*	
Mean	7118,212121	Mean	3288,977273
Standard Error	628,5551949	Standard Error	214,3405369
Median	5099	Median	2564,5
Mode	#N/A	Mode	2208
Standard Deviation	7221,549388	Standard Deviation	2462,585284
Sample Variance	52150775,56	Sample Variance	6064326,282
Kurtosis	0,332091392	Kurtosis	4,965174894
Skewness	1,034171983	Skewness	2,144718857
Range	29324	Range	13727
Minimum	17	Minimum	465
Maximum	29341	Maximum	14192
Sum	939604	Sum	434145
Count	132	Count	132
Confidence Level(95,0%)	1243,432111	Confidence Level(95,0%)	424,0167107

Table 2 Descriptive statistics of monthly spare parts demand for groups A2 and B2 over a time period of 132 months.

GroupA2		*GroupB2*	
Mean	1329,560606	Mean	1615,681818
Standard Error	148,8380795	Standard Error	105,8636345
Median	710	Median	1230,5
Mode	195	Mode	1284
Standard Deviation	1710,019344	Standard Deviation	1216,28056

Sample Variance	2924166,157	Sample Variance	1479338,402
Kurtosis	5,780438527	Kurtosis	4,625685489
Skewness	2,446958132	Skewness	2,076515292
Range	8592	Range	6656
Minimum	12	Minimum	229
Maximum	8604	Maximum	6885
Sum	175502	Sum	213270
Count	132	Count	132
Confidence Level(95,0%)	294,437225	Confidence Level(95,0%)	209,4235216

This specific analysis provides a summary of the tendency and dispersion for each group. It is evident that the mean demand for spare parts related to the transmission drive system of transport vehicles (Groups A1 and B1) is higher than spare parts related to the operating system of the vehicle engine (Groups A2 and B2). Additionally, group A1 has the highest mean (7118.212121) and standard deviation (7221.549388) among all groups of spare parts. Therefore, the average demand for spare parts and the dispersion around the mean are higher for the transport vehicles moving by track shoe with the subcategory of the transmission drive system compared to other categories of this case study. The fleet of crawler vehicles, maintenance policy, and the frequency of breakdowns that are in need of repair are considered perceived as some of the reasons which cause increased demand for spare parts.

Furthermore, groups A2 and B2 have means 1329.560606 and 1615.681818 respectively but differ significantly in standard deviation (1710.019344 and 1216.28056 respectively). The average demand for spare parts of the engine systems (subcategory “2”) is approximately equal due to the similar maintenance policy between two types of vehicle.

Moreover, the datasets of B1, A2, and B2 have higher skewness and kurtosis than group A1. It is known that kurtosis measures how much data clusters around the mean, indicating the "peakedness" or "flatness" of the distribution compared to a normal distribution. In these cases, positive kurtosis demonstrates a peaked distribution. Similarly, skewness measures the asymmetry, and positive values illustrate that the distribution is skewed to the right.

Generally, the values of means, medians, modes, kurtosis, and skewness suggest that the datasets do not follow a normal distribution. Additionally, the high values of standard deviation, variance, and range across all datasets indicate significant volatility in the demand values.

Another tool that provides a visual figure of the dataset's behavior is the time plot and box plot. These types of graphical representations can be used to analyze the variability of spare parts demand across the 132-month time, to identify potential outliers and the main components of demand such as trend, seasonality, and noise. The corresponding graphs are shown below.

To begin with, the time plot represents the time series of each dataset. This type of graphic provides information about tendency and seasonality in time series analysis.

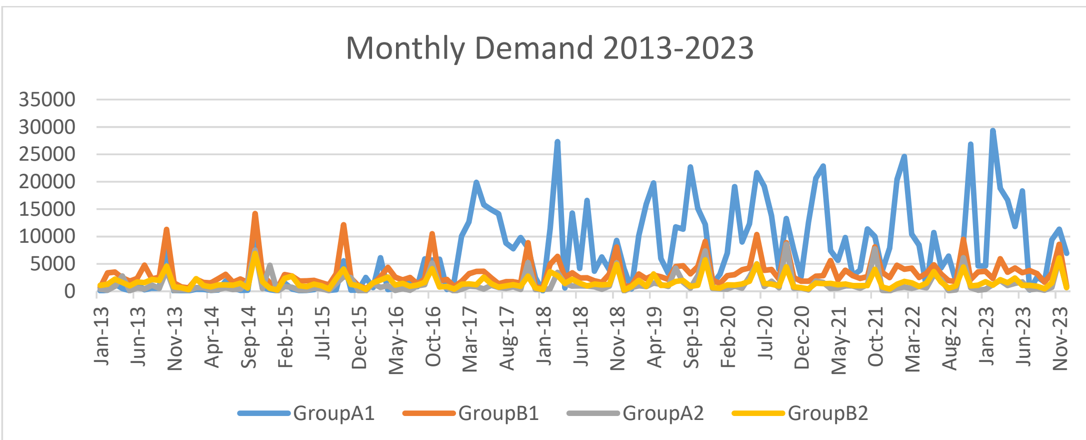

Figure 7 Time plot ofmonthlydemand: 2013-2023

According to the pattern, there is no significant upward or downward trend over time for datasets B1, A2 and B2. Instead, the data exhibits a horizontal or flat trend, indicating that the demand values have remained relatively constant over the period, except for group A1 which shows increased demand from 2017 to 2023.

Regarding seasonality in this specific time period, it can be observed an almost repeating pattern of increasing and decreasing values in groups B1, A2, and B2. Actually, these datasets exhibit the same graphic pattern. The demand for spare parts clearly increases cyclically every October-November for each year except for 2020. In this particular year, a significant increasing demand in June could be observed similar to the two aforementioned months (October-November). The same pattern occurred for group A1 until 2016, but in the following years, random demand fluctuations can be identified. In other words, it is illustrated a pattern without seasonality but with noise.

Additionally, the following time plot llustrates the cumulative demand per month for each group of spare parts.It is obvious that the cumulative demand for all datasets increases in June and October. Therefore, it is confirmed the aforementioned observation for these two months.

Subsequently, the corresponding box plots for each spare parts group are presented below.

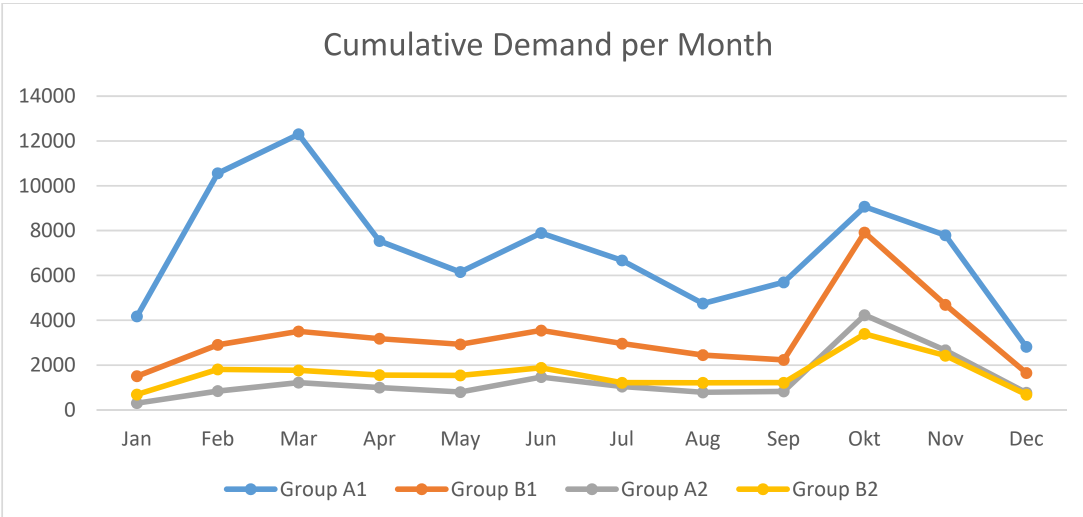

Figure 8 Time plot ofcumulative demand per month: 2013-2023

Descriptive statistics confirm the presence of outliers in groups B1, A2, and B2 taking into account the values of the corresponding interquartile range ($IQR = Q_3 - Q_1$).

Additionally, in October, the mean demand for groups B1, A2, and B2 is higher than in other months, except for group A1, where the highest value is observed in March. Moreover, the demand for spare parts related to the engine system (A2 and B2) exhibits cumulatively less volatility than the other groups related to the transmission drive system (A1 and B1).

From all the above observations, it can be concluded that the demand for spare parts related to the engine system (A2 and B2) exhibits less random fluctuation than those groups that include spare parts of the transmission drive system (A1 and B1). One explanation is the strictly defined engine maintenance policy framework from each manufacturing company compared to the transmission system. Apart from that, the higher values of demand for spare parts in groups A1 and B1 indicate more frequent failures of the transmission system of vehicles rather than their engines. Moreover, the increased demand in October and November for all datasets may be linked to many planned military activities in the given time period. Also, the flat trend reveals a stable fleet of military vehicles over time. As for the noise observed in group A1, from 2017 to 2023, it would be preferable to look for additional information or facts within the organisation that could explain the high degree of random fluctuation. Finally, the time period of the COVID-19 pandemic does not seem to have affected the demand for spare parts for military vehicles.

4.3 Moving Average

As mentioned in the previous chapter, a simple moving average (SMA) is another forecasting technique for time series. In this case study, three different window sizes (3, 6, and 12 months) for each of the four groups for ten years of historical data will be used. The demand and the forecasting error could be calculated using the suitable formula (equation 3.1) and the function: error = actual demand - forecasting demand, respectively. The results are presented in Appendix A.

To compare the results of the forecasting performance of SMA (3), SMA (6), and SMA (12) models, the Mean Absolute Percentage Error (MAPE) criterion will be implemented. The formula for calculation is as follows:

$MAPE = \frac{1}{T}\sum_{t=1}^{T}|\hat{e_t}| \,/\, Y_t$ *(equation 4.1)*

Y_t : *Actual observation*

$\hat{e_t}$: *Forecasting error*

T : *Size of the prediction sample*

MAPE is expressed as a percentage and it is considered a measure of the accuracy of forecating method. The lower the values, the higher the accuracy of the forecasting applications. Using the datasets and the aforementioned equations, the following results are shown below.

Table 3 Outcome of MAPE for spare parts demand

Outcomes	MAPE		
Moving Average	SMA(3)	SMA(6)	SMA(12)
Group A1	337,64%	333,00%	316,82%
Group B1	94,56%	75,76%	67,34%
Group A2	644,32%	451,06%	339,20%
Group B2	106,43%	85,30%	79,75%

It is apparent that for groups A1 and A2, the MAPE is very high, indicating very poor forecasting accuracy. Groups B1 and B2 have lower values of this criterion, providing better performance than the other two groups. Another observation is that the MAPE decreases as the window size increases for all groups, improving the forecast accuracy.

Moreover, time plot graphs could be created in order to visualize the forecasting method across the four different groups of spare parts.

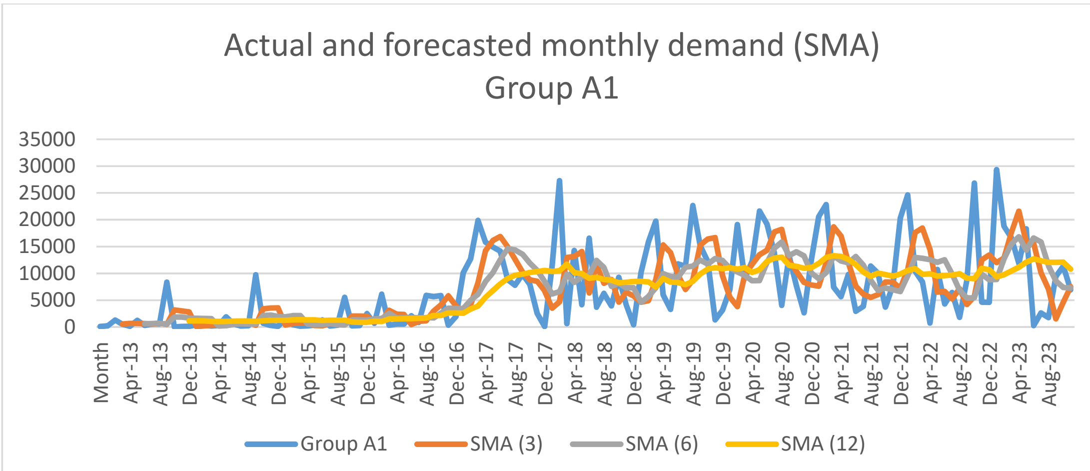

Figure 9 Time Plot of actual against forecasted monthlydemand (SMA) for group A1

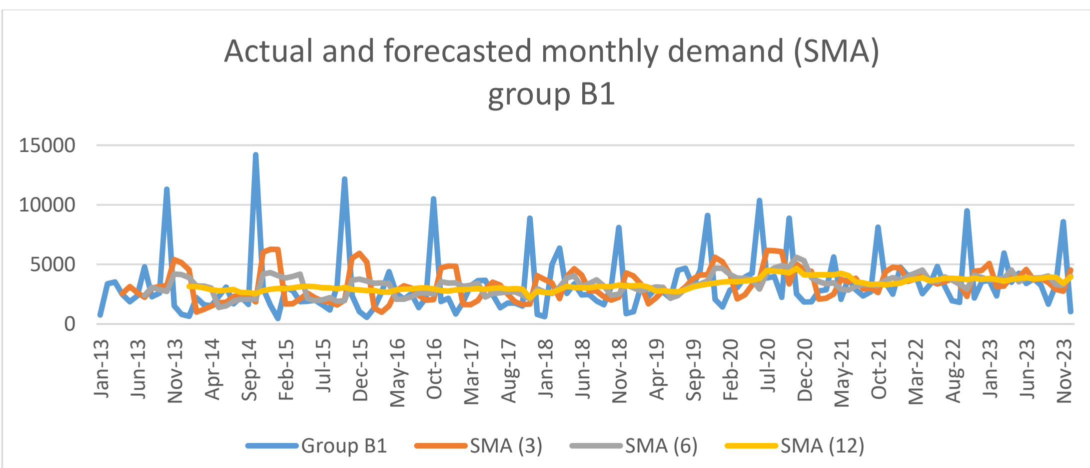

Figure 10 Time Plot of actual against forecasted monthlydemand (SMA) for group B1

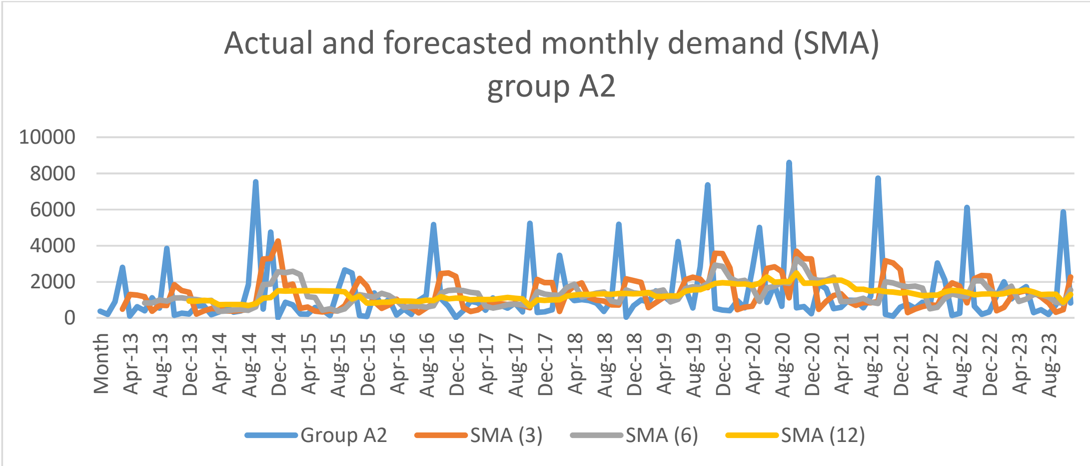

Figure 11 Time Plot of actual against forecasted monthlydemand (SMA) for group A2

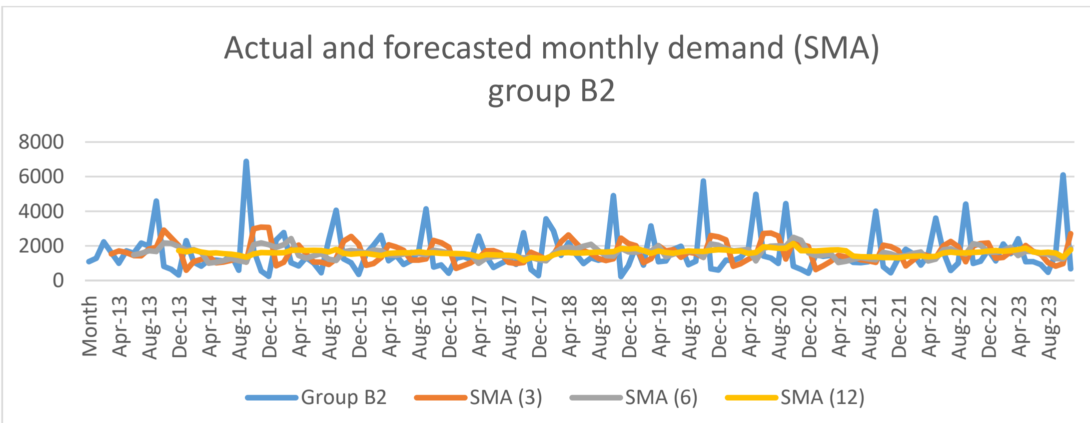

Figure 12 Time Plot of actual against forecasted monthlydemand (SMA) for group B2

First of all, high variability and frequent spikes in actual demand can be seen. The SMA (3) aligns more closely with the actual values (blue line) compared to the others, SMA (6) and SMA (12). As the moving average period increases (6 and 12 months), the delay becomes more pronounced in connection with the actual demand changes. Overall, the three SMA lines reflect the trend of actual demand, each exhibiting different levels of delay and smoothing.

The graphs of groups A1 and A2 illustrate the high variability and erratic spikes in demand, leading to larger deviations from the SMA lines. Occassionally, the lines lag significantly behind or overshoot the actual demand spikes. This makes the SMA models unable to capture the trend and seasonality well. In combination with the high MAPE values, this indicates their poor forecasting ability.

As for the graphs of groups B1 and B2~~,~~ a more predictable demand pattern can be depicted compared to groups A1 and A2. Their moving average models capture the demand trend better across the SMA models of groups A1 and A2. They are regarded as more effective forecasting models given the lower MAPE values and the closer fit of SMA lines to actual demand.

In summary, given the high MAPE values in combination with the graphs, it can be concluded that the SMA models provide some level of forecasting demand. Their accuracy is limited due to high variability and spikes. A longer window size offers smoother trends but decreases the ability to capture rapid changes in actual demand. Thus, other forecasting techniques wil be adopted to capture the actual demand more accurately, making the models perform more precisely than the previous ones.

4.4 Regression analysis

It was mentioned in the previous chapter that regression analysis helps researchers in understanding how changes in one independent variable affect the dependent variable while keeping the other independent variables constant. In this case study, the dependent variable is the demand for spare parts of military vehicles. By using excel and based on actual monthly demand, a regression analysis for each group of spare parts will be carried out in order to identify patterns and an attempt will be made to confirm or refute the existence of trends, seasonality, autoregression, and any other significant statistical inferences. The outcomes may provide useful information to decision-makers for accurate future forecasting.

Firstly, as the estimation sample is selected the 132 monthly observations from 2013 to 2023. The simple linear regression analysis is performed by taking into consideration only the monthly demand. The outcomes of each of the four groups, A1, B1, A2, and B2, are represented in the following tables.

Table 4 Summary outpout for group A1

Regression Statistics	
Multiple R	0,644056
R Square	0,414808
Adjusted R Square	0,410306
Standard Error	1,327757
Observations	132

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	162,4535	162,4535	92,1492	8,04E-17
Residual	130	229,1822	1,76294		
Total	131	391,6357			

	Coefficient	*Standard Error*	*t-stat*	*P-Value*	*Lower 95%*	*Upper 95%*
Intercept	6,004204	0,232452	25,82982	4,87E-53	5,544325	6,464083
X1	0,029114	0,003033	9,599437	8,04E-17	0,023114	0,035115

Table 5 Summary outpout for group B1

Regression Statistics	
Multiple R	0,278294
R Square	0,077447
Adjusted R Square	0,070351
Standard Error	0,624464
Observations	132

ANOVA

	df	SS	MS	F	Significance F
Regression	1	4,255729	4,255729	10,91337	0,001234
Residual	130	50,69423	0,389956		
Total	131	54,94996			

	Coefficient	Standard Error	t-stat	P-Value	Lower 95%	Upper 95%
Intercept	7,57148	0,109326	69,25607	1,74E-104	7,355192	7,787768
Linear trend	0,004712	0,001426	3,303538	0,001234	0,00189	0,007534

Table 6 Summary outpout for group A2

Regression Statistics	
Multiple R	0,183959
R Square	0,033841
Adjusted R Square	0,026409
Standard Error	1,126615
Observations	132

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	5,779446	5,779446	4,5533962	0,034731
Residual	130	165,0039	1,26926		
Total	131	170,7833			

	Coefficient	*Standard Error*	*t-stat*	*P-Value*	*Lower 95%*	*Upper 95%*
Intercept	6,222635	0,197238	31,54886	8,78E-63	5,832423	6,612847
Linear trend	0,005491	0,002573	2,133869	0,0347313	0,0004	0,010583

Table 7 Summary outpout for group B2

Regression Statistics	
Multiple R	0,027998
R Square	0,000784
Adjusted R Square	-0,0069
Standard Error	0,655869
Observations	132

ANOVA

	df	SS	MS	F	Significance F
Regression	1	0,043869	0,043869	0,101983	0,749976
Residual	130	55,92141	0,430165		
Total	131	55,96528			

	Coefficient	Standard Error	t-stat	P-Value	Lower 95%	Upper 95%
Intercept	7,138038	0,114824	62,16503	1,45E-98	6,910872	7,365203
Linear trend	0,000478	0,001498	0,319348	0,749976	-0,00249	0,003442

From the above results, it can be seen that the values of R-squared for each group A1, B1, A2, and B2, are 0.41, 0.07, 0.03, and 0.001, respectively. It is known that values close to 1 indicate a very good model fit. In these cases, the forecasting models for groups B1, A2, and especially for B2 have approximately zero R-squared values, indicating that the models have a very poor fit. The exception is group A1, where the forecasting model explains 41.48% of the variability in the demand variable. However, it is still considered a model of a relatively weak explanatory power.

Additionally, it appears that the F-statistic is relatively high and the p-value is very low for forecasting models A1 and B1, indicating that their variables are statistically significant. The model for group A2 has F-statistic with a p-value of 0.03473 which is just below the significance level of 5%, indicating that it is statistically marginally significant. For the forecasting model B2, the p-value of the F-statistic is equal to 0.74998 (> 0.05), which means that it is not statistically significant.

Regarding the predictors, which are the intercept and the independent variable for each group of spare parts, they are statistically significant due to their low p-values, except for the independent variable of the forecasting model for group B2, which is almost equal to zero, indicating that there is no effect on the dependent variable.

Therefore, taking into account all the above outcomes, the forecasting models for spare parts groups B1, A2, and B2 have very low explanatory power, except for A1. This means that there are factors that the models do not include and influence the dependent variable. In conclusion, the aforementioned forecasting models are considered inaccurate and should not be recommended to decision-makers.

Furthermore, using the above outcomes for each forecasting model, the estimated monthly demand can be calculated and the corresponding graphs between actual and estimated values can be created. As illustrated below, each forecasting model sometimes overestimates and other times underestimates the actual monthly demand, confirming the poor fit of each model.

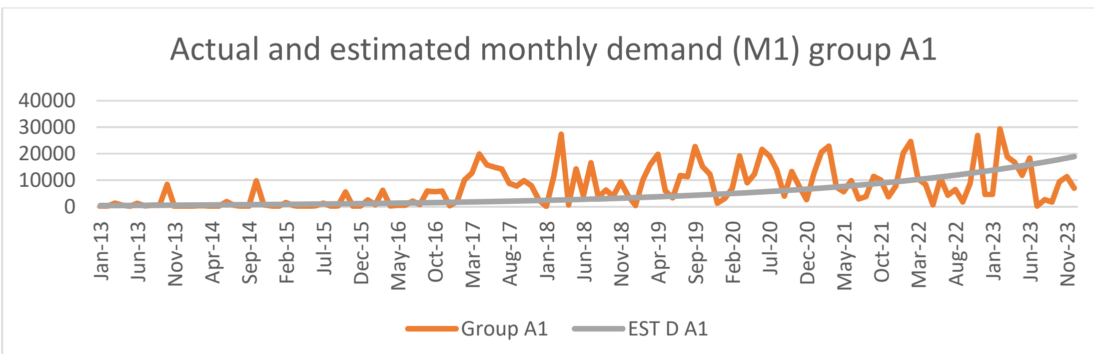

Figure 13 Time Plot ofactual and estimated monthlydemand (M1) for group A1 (2013-2023)

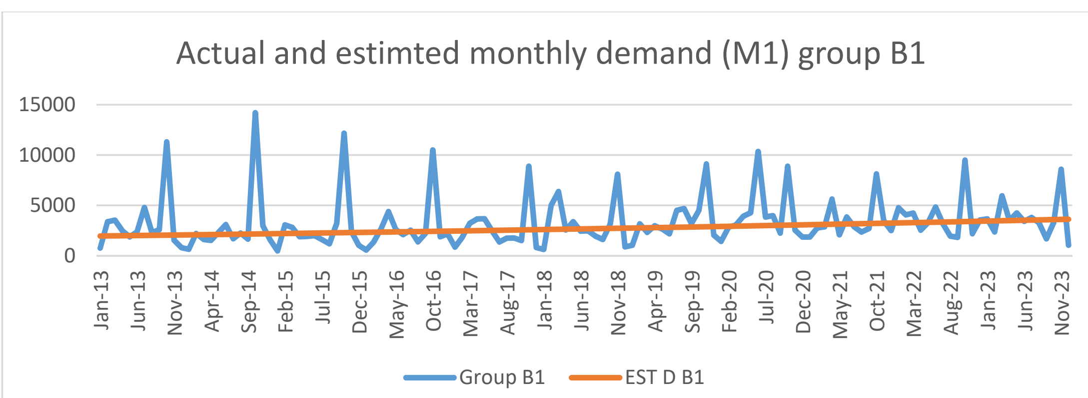

Figure 14 Time Plot ofactual and estimated monthlydemand (M1) for group B1 (2013-2023)

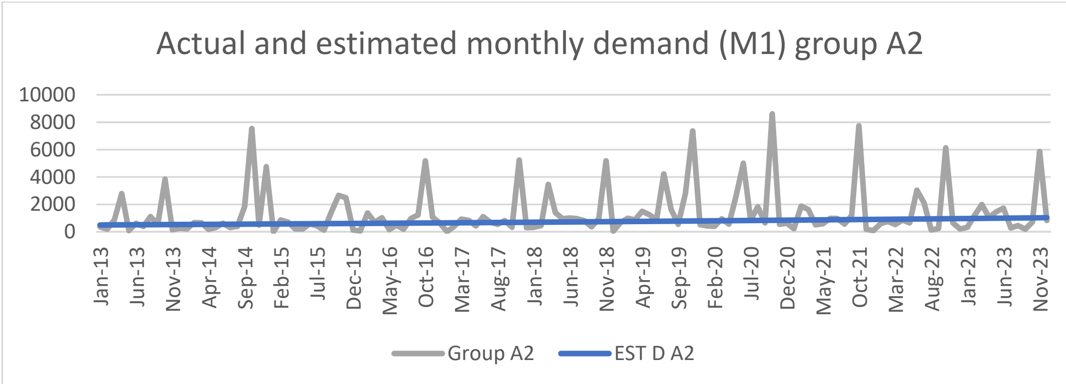

Figure 15 Time Plot ofactual and estimated monthlydemand (M1) for group A2 (2013-2023)

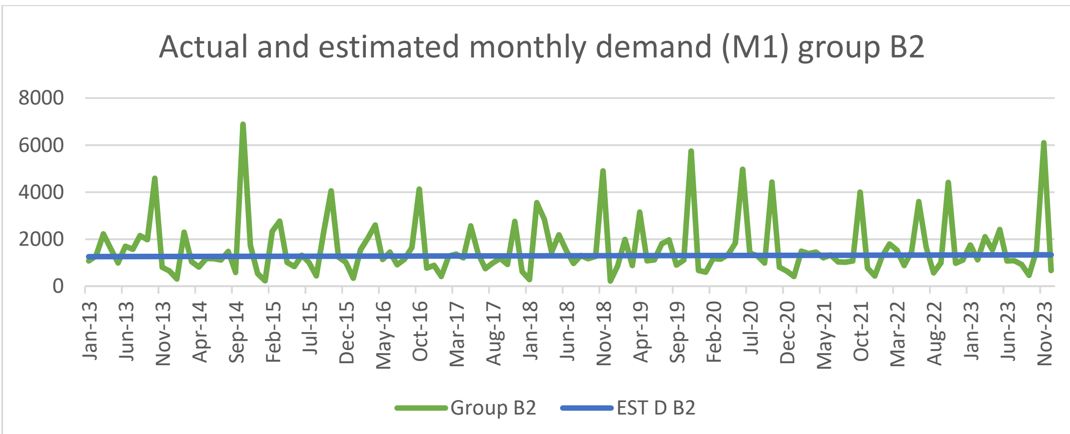

Figure 16 Time Plot ofactual and estimated monthlydemand (M1) for group B2 (2013-2023)

To continue with regression analysis for each of the four groups in order to examine if there is a correlation among them, first, group A1 taken as the dependent variable and the other three groups as independent variables will be studied by using excel. In the following table, the results of regression analysis for group A1 are presented while the other three groups are listed in appendix A.

Table 8 Summary outpout for group A1 and variables B1, A2 and B2

Regression Statistics	
Multiple R	0,738746
R Square	0,545746
Adjusted R Square	0,531439
Standard Error	1,183555
Observations	132

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	213,7337	53,43343	38,14486	6,17E-21

Residual	127	177,902	1,400803
Total	131	391,6357	

	Coefficient	*Standard Error*	*t-stat*	*P-Value*	*Lower 95%*	*Upper 95%*
Intercept	-0,33671	1,368146	-0,2461	0,805999	-3,04402	2,370607
Linaer trend	0,024595	0,003094	7,948938	8,82E-13	0,018473	0,030718
LN B1	0,660118	0,334306	1,974596	0,050484	-0,00141	1,321649
LN A2	0,259809	0,139437	1,863276	0,064733	-0,01611	0,535729
LN B2	-0,03837	0,34372	-0,11162	0,9113	-0,71853	0,641794

The model is statistically significant (p-value: 6.17E-21) and explains 54.6% of the variability in the dependent variable. The variables 'LN B1', 'LN A2', and 'LN B2' (monthly demand of groups B1, A2, and B2) are considered almost not significant according to their p-values.-These specific results were anticipated, taking into account that the four datasets of spare parts are distinct and independent from each other.However, the outputs from the other three regression analyses (with B1, A2, and B2 as independent variables, respectively) do not reach the same conclusions as far as the correlation between the dependent and independent variables is concerned. Even though the values of Multiple R and R-Square for each model are relatively high, additional variables need to be considered and examined.

Next, dummy variables will be used in order to try to understand the historical demand patterns and discover the relationship between the dependent and independent variables.

4.5 Regression analysis with dummy variables

In order to improve the aforementioned forecasting models dummy variables [j_t where $t = 2\ (February), 3(March) \dots 12(December)$] will be adopted in regression analysis. In this process, an attempt will be made so as potential seasonal patterns in monthly demand could be captured and the fit of each forecasting model could be improved.

Table 9 Summary outpout for group A1

Regression Statistics	
Multiple R	0,989409
R Square	0,978929
Adjusted R Square	0,968401
Standard Error	1,242156
Observations	132

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*

Regression	13	8530,422	656,1863	425,2799	1,75E-92
Residual	119	183,6112	1,542952		
Total	132	8714,033			

	Coefficient	*Standard Error*	*t-stat*	*P-Value*	*Lower 95%*	*Upper 95%*
Constant term	5,105794	0,412884	12,36617	4,28E-23	4,288243	5,923345
linear trend	0,029298	0,002849	10,28328	3,91E-18	0,023657	0,03494
j2	1,455164	0,529665	2,74733	0,006943	0,406375	2,503953
j3	1,785134	0,529688	3,370163	0,001013	0,7363	2,833969
j4	0,748636	0,529726	1,41325	0,160193	-0,30027	1,797546
j5	0,612263	0,52978	1,155693	0,250122	-0,43675	1,661279
j6	1,239276	0,529849	2,338925	0,021007	0,190123	2,28843
j7	0,852475	0,529933	1,608646	0,110344	-0,19685	1,901795
j8	0,583823	0,530032	1,101486	0,272908	-0,46569	1,633341
j9	0,734281	0,530147	1,385052	0,168628	-0,31546	1,784026
j10	1,890303	0,530277	3,564744	0,000525	0,840301	2,940306
j11	0,780866	0,530423	1,472157	0,143618	-0,26942	1,831156
j12	-0,04796	0,530584	-0,09039	0,928129	-1,09857	1,002649

Table 10 Summary outpout for group B1

Regression Statistics	
Multiple R	0,998386
R Square	0,996774
Adjusted R Square	0,988046
Standard Error	0,473218
Observations	132

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	13	8234,846	633,4497	2828,723	1,6E-140
Residual	119	26,64825	0,223935		
Total	132	8261,494			

	Coefficient	*Standard Error*	*t-stat*	*P-Value*	*Lower 95%*	*Upper 95%*
Constant term	6,731193	0,157294	42,79366	4,08E-74	6,419735	7,042652
linear trend	0,004505	0,001085	4,150919	6,25E-05	0,002356	0,006655
j2	0,905875	0,201784	4,489339	1,66E-05	0,506323	1,305426
j3	1,073735	0,201792	5,320989	4,92E-07	0,674166	1,473304
j4	0,980921	0,201807	4,860691	3,61E-06	0,581323	1,380519
j5	0,91579	0,201827	4,53749	1,37E-05	0,516151	1,315428
j6	1,010616	0,201854	5,006679	1,94E-06	0,610926	1,410307
j7	0,881568	0,201886	4,36667	2,71E-05	0,481814	1,281322
j8	0,682615	0,201924	3,38056	0,000979	0,282786	1,082444

j9	0,636817	0,201967	3,153066	0,002045	0,236901	1,036732
j10	1,743544	0,202017	8,630679	3,19E-14	1,34353	2,143558
j11	1,183407	0,202072	5,856352	4,29E-08	0,783283	1,58353
j12	0,233598	0,202134	1,155659	0,250136	-0,16665	0,633842

Table11 Summary outpout for group A2

Regression Statistics	
Multiple R	0,99063
R Square	0,981347
Adjusted R Square	0,971063
Standard Error	0,961628
Observations	132

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	13	5789,449	445,3422	481,5922	1,34E-95
Residual	119	110,0427	0,924729		
Total	132	5899,492			

	Coefficient	*Standard Error*	*t-stat*	*P-Value*	*Lower 95%*	*Upper 95%*
Constant term	4,912975	0,319638	15,37041	4,88E-30	4,280059	5,545891
linear trend	0,004992	0,002206	2,263316	0,025429	0,000625	0,00936
j2	1,337412	0,410046	3,261618	0,001446	0,525481	2,149343
j3	1,713951	0,410063	4,179721	5,6E-05	0,901984	2,525917
j4	1,413419	0,410093	3,446582	0,000785	0,601394	2,225445
j5	1,031888	0,410135	2,515974	0,013203	0,21978	1,843995
j6	1,766722	0,410188	4,307105	3,42E-05	0,954509	2,578936
j7	1,290695	0,410253	3,146095	0,002091	0,478353	2,103038
j8	1,123767	0,41033	2,738689	0,007117	0,311272	1,936262
j9	1,251032	0,410419	3,048181	0,002837	0,438361	2,063703
j10	2,69926	0,41052	6,575223	1,36E-09	1,886389	3,51213
j11	1,898697	0,410632	4,623836	9,64E-06	1,085604	2,711791
j12	0,587529	0,410757	1,430357	0,155235	-0,22581	1,400869

Table12 Summary outpout for group B2

Regression Statistics	
Multiple R	0,997651
R Square	0,995308
Adjusted R Square	0,986431
Standard Error	0,519394
Observations	132

ANOVA

	df	SS	MS	F	Significance F
Regression	13	6809,561	523,8123	1941,696	6,2E-131
Residual	119	32,1027	0,269771		
Total	132	6841,663			

	Coefficient	Standard Error	t-stat	P-Value	Lower 95%	Upper 95%
Constant term	6,301368	0,172643	36,49941	1,79E-66	5,959518	6,643219
linear trend	0,000402	0,001191	0,337219	0,736546	-0,00196	0,002761
j2	1,113958	0,221474	5,029751	1,76E-06	0,675418	1,552498
j3	1,079895	0,221483	4,875739	3,39E-06	0,641336	1,518454
j4	0,940563	0,221499	4,246347	4,33E-05	0,501972	1,379154
j5	0,943865	0,221522	4,260824	4,1E-05	0,50523	1,382501
j6	1,076534	0,221551	4,859086	3,63E-06	0,637841	1,515226
j7	0,73873	0,221586	3,33383	0,001142	0,299967	1,177492
j8	0,678364	0,221627	3,060832	0,002729	0,23952	1,117209
j9	0,67432	0,221676	3,041923	0,002893	0,23538	1,113259
j10	1,608021	0,22173	7,252162	4,51E-11	1,168974	2,047069
j11	1,124986	0,221791	5,072286	1,46E-06	0,685818	1,564154
j12	0,122002	0,221858	0,549912	0,58341	-0,3173	0,561303

From the above summary outcomes of regression analysis for each spare parts group, a reference to the most significant observations will be made.

For group A1, the high value of R-square (0.9789) indicates a very good fit for the model, explaining 97.89% of the variability in the dependent variable. Moreover, the p-value (1.75E-92) confirms the significance of the overall regression. Regarding the coefficients, the high p-values of the constant term, linear trend, j2 (February), j3 (March), j6 (June), and j10 (October) indicate a positive linear trend over time and a significant effect in the base month (January). In summary, the seasonal effect compared to the base month and the upward trend in spare parts demand are confirmed.

Next, the results concerning group B1 will be stated. In a similar way, as with the abovementioned findings, the very high value of R-square and the corresponding p-value for the overall regression confirm the excellent fit of the model. The positive value of the linear trend coefficient also indicates an upward trend over time. The seasonal effects are confirmed by the p-values for all months except December compared to the base month.

The next group of spare parts is A2 where the same observations apply to the forecasting model for group B1. All the variables except j12 (December) are statistically significant predictors at the 0.05 level, explaining 98.13% of the variability in the dependent variable.

Finally, the outcomes of the regression analysis for group B2 indicate the same conclusions as the previous spare parts group A2, apart from the linear trend variable, where the p-value is not statistically significant at the 0.05 level. Thus, the upward trend is not confirmed.

Furthermore, by using the above outcomes for each forecasting model with dummy variables, the estimated monthly demand can be calculated and the respective graphs comparing actual and estimated values can also be created, including the results from model M1. As illustrated below, each forecasting model M2 sometimes overestimates and at other times underestimates the actual monthly demand, yet confirming the very good fit of each model.

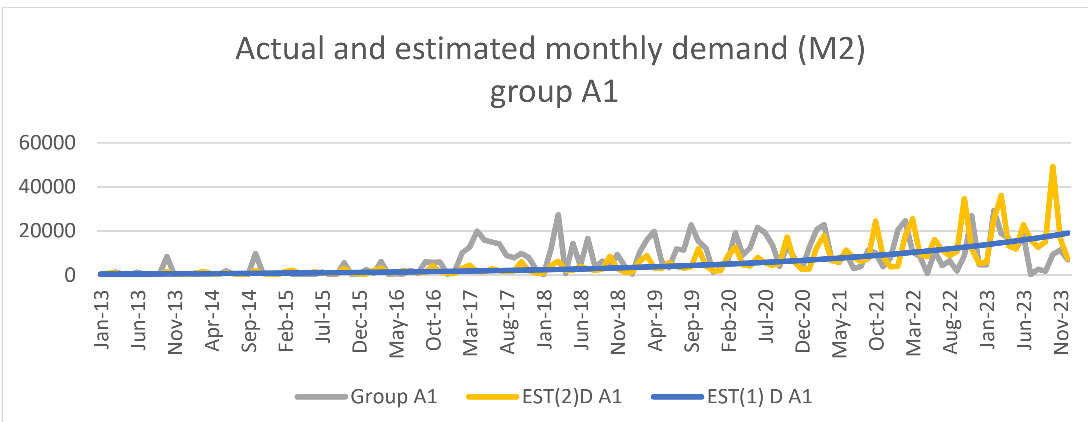

Figure 17 Time Plot ofactual and estimated monthlydemand (M2) group A1 (2013-2023)

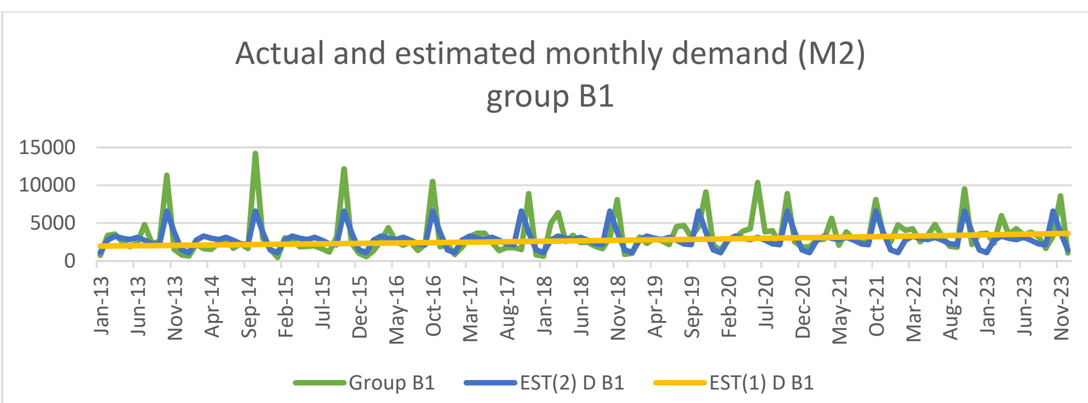

Figure 18 Time Plot ofactual and estimated monthlydemand (M2) group B1 (2013-2023)

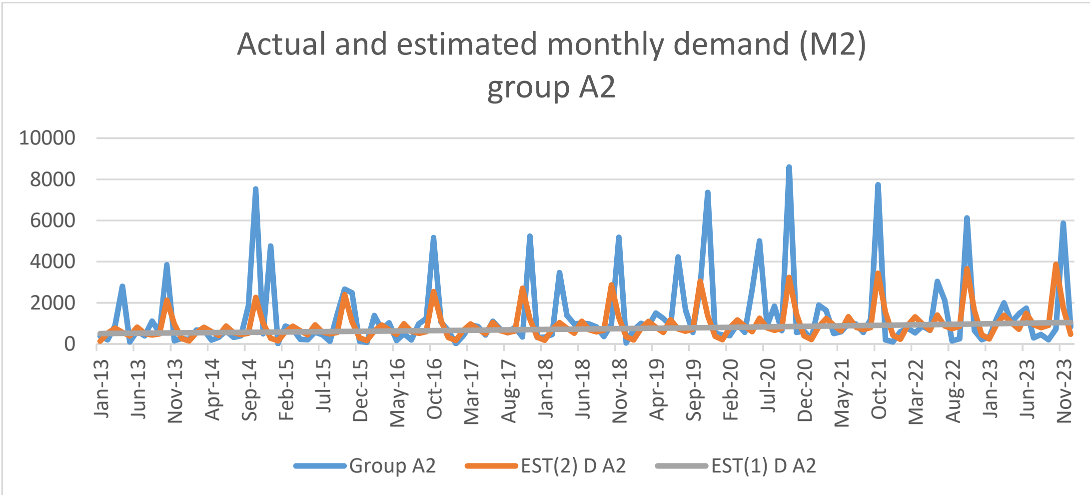

Figure 19 Time Plot ofactual and estimated monthlydemand (M2) group A2 (2013-2023)

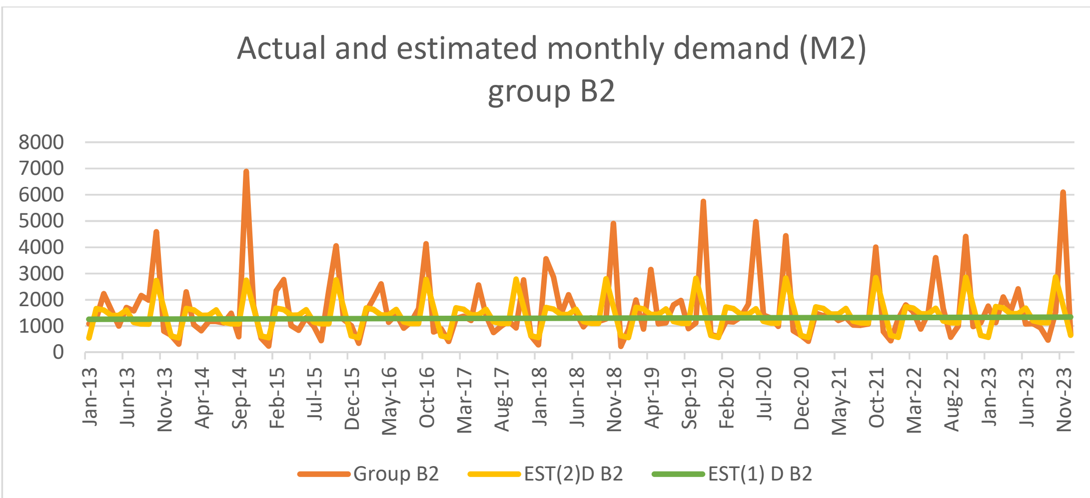

Figure 20 Time Plot ofactual and estimated monthlydemand (M2) group B2 (2013-2023)

Comparing all the aforementioned outcomes, graphs, and observations, it is obvious that the forecasting model (M2) including dummy variables for each group fits very well with the actual monthly demand for spare parts.

4.6 Regression analysis with dummy and lag variables

The next step is to examine the effect of dummy variables in combination with two lag variables (Y_{t-1} previous and Y_{t-2} second previous monthly demand) in regression analysis. An attempt will be made to confirm or refute the previous conclusions about trends and seasonality. The outcomes for each group (A1, B1, A2, and B2) are presented analytically in Appendix A (tables 7-14) using the lag variable Y_{t-1} and Y_{t-2} for forecasting models M3 and M4, respectively.

From all the outcomes of the regression analyses, high values of Multiple R and R-square are observed, indicating a very good fit for all the models, each explaining approximately 99% of the variability in the dependent variable.

Furthermore, the positive values and the p-values of the linear trend coefficient confirm an upward trend over time for groups A1, B1, and A2, apart from B2 (p-value > 0.05).

Additionally, it is confirmed that all the dummy variables, except for j12 (December), are statistically significant, indicating that the months have a great impact on the independent variable for groups A2 and B2. For group A1, some dummy variables (j2, j3 and j10) are statistically significant, as found in the previous forecasting model M2. Thus, the seasonal effects are confirmed by the p-values of the dummy variables.

Finally, the lag variables Y_{t-1} and Y_{t-2} are statistically significant only for group A1 and B2, indicating a significant effect of the previous and second previous time periods on the forecasting demand. In the other two groups, the lag variables do not contribute to the variation in monthly demand for spare parts.

4.7 Comparative outcomes of regression analysis

In order to focus on the most significant outcomes from the above forecasting models, we a pivot table has been created. This table contains the results of model M1, M1.1 (A1, B1, A2 and B2 variables), M2 (dummy variables), M3 [dummy and first order (Y_{t-1}) lag variables], and M4 [dummy, first order (Y_{t-1}) and second order (Y_{t-2}) lag variables]. By comparing these values, it is aimed to suggest the most accurate forecasting model for all groups of spare parts.

Table 13 Pivot outpouts from models M1, M1.1, M2, M3 and M4

	M1				M1.1			
Model	A1	B1	A2	B2	A1	B1	A2	B2
Multiple R	0,6441	0,2783	0,1840	0,0280	0,6441	0,2783	0,1840	0,8878
R-Square	0,4148	0,0774	0,0338	0,0008	0,4148	0,0774	0,0338	0,7882
Observations	132	132	132	132	132	132	132	132
F-Statistic	92,1492	10,9134	4,5534	0,1020	92,1492	10,9134	4,5534	118,1279
Significance F	0,0000	0,0012	0,0347	0,7500	0,0000	0,0012	0,0347	0,0000
Constant term	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0243

Linear trend	0,0000	0,0012	0,0347	0,7500	0,0000	0,0012	0,0347	0,0001
LN A1						0,0505	0,0647	0,9113
LN B1					0,0505		0,1968	0,0000
LN A2					0,0647	0,1968		0,0000
LN B2					0,9113	0,0000	0,0000	

	M2				M3				M4			
Model	**A1**	**B1**	**A2**	**B2**	**A1**	**B1**	**A2**	**B2**	**A1**	**B1**	**A2**	**B2**
Multiple R	0,9894	0,9984	0,9906	0,9977	0,9904	0,9984	0,9909	0,9978	0,9912	0,9984	0,9909	0,9978
R-Square	0,9789	0,9968	0,9813	0,9953	0,9808	0,9968	0,9818	0,9955	0,9825	0,9968	0,9819	0,9957
Observations	132	132	132	132	131	131	131	131	130	130	130	130
F-Statistic	425,28	2828,72	481,59	1941,70	427,68	2576,06	451,69	1867,46	430,16	2366,34	415,19	1762,96
Significance F	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
Coefficient	P-value				P-value				P-value			
Constant term	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0006	0,0000	0,0000	0,0000
Linear trend	0,0000	0,0001	0,0254	0,7365	0,0000	0,0001	0,0083	0,5404	0,0008	0,0002	0,0175	0,5558
j2	0,0069	0,0000	0,0014	0,0000	0,0093	0,0001	0,0015	0,0000	0,0011	0,0005	0,0015	0,0001
j3	0,0010	0,0000	0,0001	0,0000	0,0196	0,0000	0,0000	0,0000	0,0025	0,0000	0,0000	0,0000
j4	0,1602	0,0000	0,0008	0,0000	0,8013	0,0000	0,0001	0,0000	0,8207	0,0000	0,0002	0,0000
j5	0,2501	0,0000	0,0132	0,0000	0,5534	0,0000	0,0036	0,0000	0,8330	0,0000	0,0040	0,0000
j6	0,0210	0,0000	0,0000	0,0000	0,0640	0,0000	0,0000	0,0000	0,0383	0,0000	0,0000	0,0000
j7	0,1103	0,0000	0,0021	0,0011	0,4481	0,0001	0,0004	0,0001	0,2635	0,0001	0,0005	0,0000
j8	0,2729	0,0010	0,0071	0,0027	0,6313	0,0015	0,0020	0,0002	0,6728	0,0017	0,0022	0,0001
j9	0,1686	0,0020	0,0028	0,0029	0,3568	0,0029	0,0009	0,0003	0,2936	0,0033	0,0009	0,0004
j10	0,0005	0,0000	0,0000	0,0000	0,0030	0,0000	0,0000	0,0000	0,0009	0,0000	0,0000	0,0000
Jj1	0,1436	0,0000	0,0000	0,0000	0,7992	0,0000	0,0000	0,0000	0,5242	0,0000	0,0000	0,0000
j12	0,9281	0,2501	0,1552	0,5834	0,5008	0,2414	0,0437	0,1044	0,2564	0,2579	0,0581	0,0308
Y_{t-1}					0,0009	0,6119	0,1103	0,0264	0,0197	0,6282	0,1463	0,0105
Y_{t-2}									0,0018	0,9498	0,8817	0,0433

Thus, it can be inferred that the above forecasting models can estimate each dependent variable with high accuracy using the independent variables. To be more specific, the most accurate model for each group is proposed as follows.

M4 for group A1: This model is recommended due to its highest values of R-Square, F-statistic, and its p-value. Most independent variables in the model, except for j4-j5 (April-May), j7-j9 (Jule-September) and j11-j12 (November-December), are significant and explain 98.25% of the variability in the dependent variable.

M2 for group B1: This model is recommended because of the high values of the same key statistical metrics. All independent variables, except for J12 (December), are significant and explain approximately 99,68% of the variability in the dependent variable. Notably, the lagged variables Y_{t-1} and Y_{t-2} are not significant at 0.05 level of significance.

M4 for group A2: This model has the highest R-Square value 98,19% making it better than the others. Notably that the dummy variable J12 (December) and first order Y_{t-1} and second order Y_{t-2} lag vaiables are not significant in model at the 0.05 level of significance.

M4 for group B2: This model is recommended because of its high values of R-Square, F-statistic, and its p-value. All independent variables, except for the linear trend are significant and explain 99.57% of the variability in the dependent variable. The aforementioned coefficients are not significant in all models at the 0.05 level of significance.

In summary, if it is necessary to suggest one type of forecasting model for all groups of spare parts, the M4 model is preferred as the most accurate in most cases and M2 as second and most practical choice.Taking into account the datasets and the aforementioned conclusions of using different techniques from time series analysis the demand incorporating the significant variables will be considered as well.

4.8 Estimated and forecasting model

The implementation of forecasting models necessitates that data be divided into two sets: an estimation sample and a forecasting sample. From the total monthly observations, 73% were allocated to the estimation sample. Consequently, the remaining 27% of observations make up the forecasting sample for each group in this case study. Next, considering the constant term the linear trend, the dummy variables and the two lag variables, the estimation model could be constructed. By examining the p-value of each variable's coefficient, those with a p-value above 0.05 are pruned. Thus, the new model was constructed, including only the statistically significant variables.

For group A1 spare parts, based on the aforementioned statistically significant variables (constant term, linear trend, j2, j3, j6, j10, Y_{t-1} and Y_{t-2}) the results of the regression analysis for the estimation sample (95 observations) in table 14 are presented.

Table 14 Summary output of estimated sample for group A1

Regression Statistics	
Multiple R	0,989836
R Square	0,979776
Adjusted R Square	0,966654

Standard Error	1,167886
Observations	95

ANOVA

	df	SS	MS	F	Significance F
Regression	8	5748,774	718,5968	526,8469	1,25E-69
Residual	87	118,6643	1,363957		
Total	95	5867,438			

	Coefficient	Standard Error	t-stat	P-Value	Lower 95%	Upper 95%
Constant term	3,438259	0,848818	4,050642	0,000111	1,751141	5,125377
linear trend	0,03169	0,007861	4,031353	0,000119	0,016066	0,047314
j2	1,22664	0,514322	2,384965	0,019252	0,204369	2,24891
j3	1,522615	0,476844	3,193112	0,00196	0,574837	2,470393
j6	0,774824	0,444676	1,742446	0,084964	-0,10902	1,658666
j10	1,712568	0,442507	3,870145	0,00021	0,833036	2,592099
Y_{t-1}	0,147746	0,099296	1,487932	0,140384	-0,04962	0,345107
Y_{t-2}	0,151029	0,10792	1,399444	0,165235	-0,06347	0,365532

Thus, the equation for forecasting demand for group A1 is:

$$\hat{Y}_t = 3{,}438259 + 0{,}03169 * LinTrend + 1{,}22664 * J2 + 1{,}522615 * J3 + 0{,}774824 * J6 + 1{,}712568 * J10 + 0{,}147746 * Y_{t-1} + 0{,}15102 * Y_{t-2}$$

Using the above equation, the values of estimated demand for the forecasting sample (35 observations) are calculated. Figure 26 depicts the actual and forecasted demand. Furthermore, the MAPE was calculated and it was found to be 20.91% indicating a good forecasting performance.

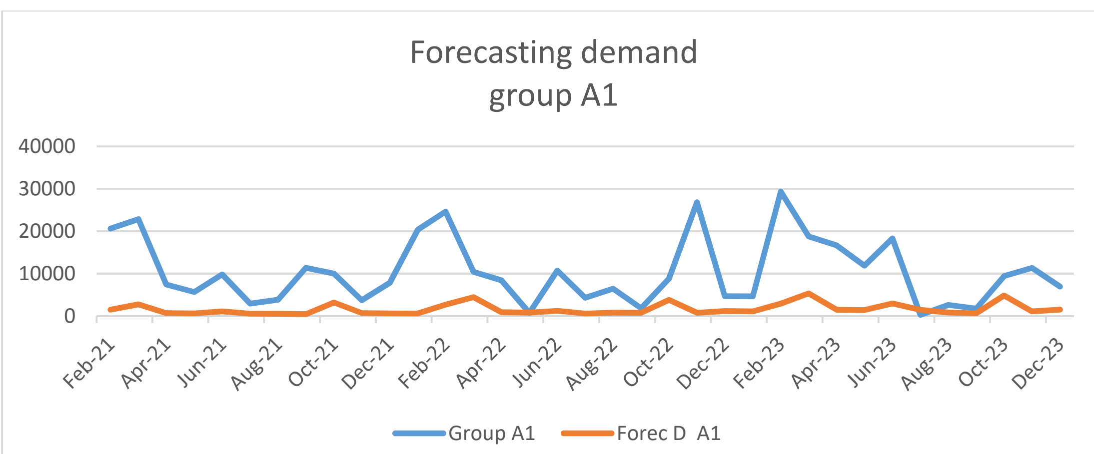

Figure 21 Time Plot ofactual and forecasting monthlydemand for group A1

For group B1 spare parts, based on the aforementioned statistically significant variables (constant term, linear trend and j2-j11), the results of the regression analysis for the estimation sample (96 observations) in table 15 are presented.

Table 15 Summary outpout of estimated sample for group B1

Regression Statistics	
Multiple R	0,998355
R Square	0,996714
Adjusted R Square	0,984379
Standard Error	0,48028
Observations	96

	df	*SS*	*MS*	*F*	*Significance F*
Regression	12	5876,555	489,7129	2123,011	7,64E-98
Residual	84	19,3762	0,230669		
Total	96	5895,931			

	Coefficient	*Standard Error*	*t-stat*	*P-Value*	*Lower 95%*	*Upper 95%*
Constant term	6,631325	0,147795	44,86829	1,81E-60	6,337418	6,925232
linear trend	0,005178	0,001777	2,914216	0,004569	0,001645	0,008712
j2	1,026789	0,208121	4,933614	4,03E-06	0,612917	1,440661
j3	1,132865	0,20806	5,444885	5,05E-07	0,719114	1,546616
j4	1,052242	0,208015	5,058494	2,45E-06	0,638582	1,465902
j5	1,031283	0,207984	4,958462	3,65E-06	0,617683	1,444883
j6	1,065932	0,207969	5,12543	1,87E-06	0,652362	1,479502
j7	0,965368	0,207969	4,641876	1,26E-05	0,551798	1,378937
j8	0,798205	0,207984	3,83781	0,00024	0,384605	1,211805
j9	0,811281	0,208015	3,90011	0,000193	0,39762	1,224941
j10	1,902481	0,20806	9,14389	3,05E-14	1,48873	2,316232
j11	1,305262	0,208121	6,271647	1,48E-08	0,89139	1,719133

Thus, the equation for forecasting demand for group B1 is:

$$\hat{Y}_t = 6{,}631325 + 0{,}005178 LinTrend + 1{,}026789 * J2 + 1{,}132865 * J3 + 1{,}052242 * J4 + 1{,}031283 * J5 + 1{,}065932 * J6 + 0{,}965368 * J7 + 0{,}798205 * J8 + 0{,}811281 * J9 + 1{,}902481 * J10 + 1{,}305262 * J11$$

Using the above equation, the values of estimated demand for the forecasting sample (36 observations) were calculated as well. Figure 27 depicts the actual and forecasted demand. Furthermore, the MAPE was calculated and it was found to be 6,25% indicating a highly accurate forecasting performance.

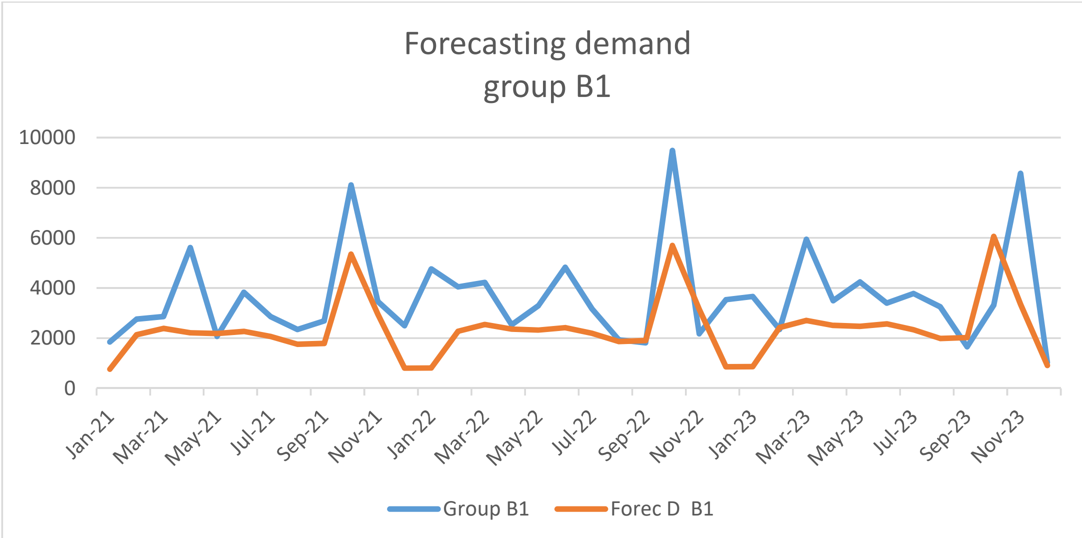

Figure 22 Time Plot ofactual and forecasting monthly demand for group B1

For group A2 spare parts, based on the aforementioned statistically significant variables (constant term, linear trend and j2-j11), the results of the regression analysis for the estimation sample (96 observations) in table 16 are presented.

Table 16 Summary outpout of estimated sample for group A2

Regression Statistics	
Multiple R	0,990366
R Square	0,980826
Adjusted R Square	0,96641
Standard Error	0,986698
Observations	96

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	12	4183,275	348,6063	358,0693	4,39E-66
Residual	84	81,78006	0,973572		
Total	96	4265,055			

	Coefficient	*Standard Error*	*t-stat*	*P-Value*	*Lower 95%*	*Upper 95%*
Constant term	4,93867	0,303634	16,26521	1,1E-27	4,334861	5,542479
linear trend	0,010913	0,00365	2,989536	0,003664	0,003654	0,018172
j2	0,939945	0,427568	2,19835	0,030675	0,089678	1,790211
j3	1,454362	0,427444	3,402464	0,001025	0,604343	2,30438
j4	1,20187	0,42735	2,812378	0,006121	0,352037	2,051702
j5	0,648106	0,427288	1,51679	0,133074	-0,2016	1,497814
j6	1,378466	0,427256	3,226319	0,001788	0,528819	2,228112
j7	0,988218	0,427256	2,312938	0,023171	0,138571	1,837864

j8	1,105518	0,427288	2,587292	0,011394	0,25581	1,955226
j9	1,211372	0,42735	2,834612	0,005746	0,361539	2,061204
j10	2,409124	0,427444	5,636121	2,27E-07	1,559105	3,259142
j11	1,781027	0,427568	4,165481	7,5E-05	0,930761	2,631294

Thus, the equation for forecasting demand for group A2 is:

$$\hat{Y}_t = 4{,}93867 + 0{,}010913 LinTrend + 0{,}939945 * J2 + 1{,}454362 * J3 + 1{,}20187 * J4 + 0{,}648106 * J5 + 1{,}378466 * J6 + 0{,}988218 * J7 + 1{,}105518 * J8 + 1{,}211372 * J9 + 2{,}409124 * J10 + 1{,}781027 * J11$$

Using the above equation, the values of estimated demand for the forecasting sample (36 observations) were calculated. Figure 28 depicts the actual and forecasted demand. Furthermore, we calculated the MAPE was calculated and found to be 13,08% indicating an almost highly accurate forecasting performance.

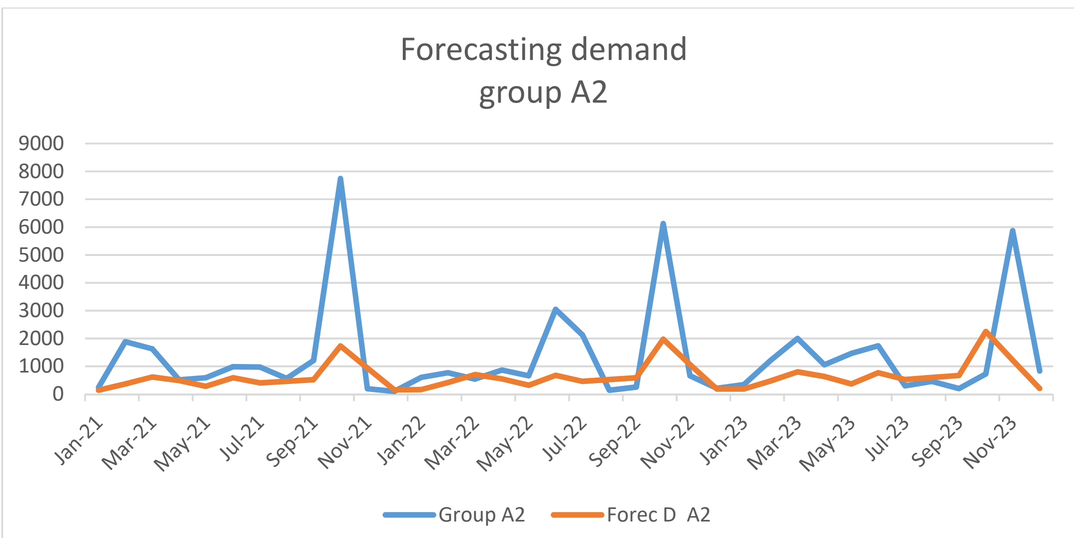

Figure 23 Time Plot ofactual and forecasting monthly demand for group A2

Finally, for group B2 spare parts, based on the aforementioned statistically significant variables (constant term, j2-j12, Y_{t-1} and Y_{t-2}), the results of the regression analysis for the estimation sample (95 observations) are presented in table 17.

Table 17 Summary outpout of estimated sample for group B2

Regression Statistics	
Multiple R	0,997956
R Square	0,995917

Adjusted R Square	0,982916
Standard Error	0,497742
Observations	95

ANOVA

	df	SS	MS	F	Significance F
Regression	14	4894,321	349,5944	1411,096	1,54E-89
Residual	81	20,06749	0,247747		
Total	95	4914,389			

	Coefficient	Standard Error	t-stat	P-Value	Lower 95%	Upper 95%
Constant term	8,647759	1,21774	7,101483	4,29E-10	6,224839	11,07068
j2	1,312238	0,290598	4,51564	2,12E-05	0,734038	1,890437
j3	1,556617	0,297451	5,233191	1,28E-06	0,964783	2,148451
j4	1,598894	0,271999	5,878307	8,87E-08	1,057701	2,140086
j5	1,471431	0,267237	5,506098	4,2E-07	0,939714	2,003148
j6	1,596597	0,263309	6,063598	4,03E-08	1,072696	2,120499
j7	1,292789	0,269298	4,800585	7,13E-06	0,75697	1,828608
j8	1,289157	0,257851	4,999624	3,26E-06	0,776115	1,802199
j9	1,27563	0,261032	4,88687	5,09E-06	0,756258	1,795002
j10	2,073457	0,260524	7,958794	9,06E-12	1,555096	2,591819
j11	1,848825	0,295402	6,258676	1,74E-08	1,261068	2,436582
j12	0,76686	0,283746	2,702634	0,008379	0,202296	1,331425
Y_{t-1}	-0,28005	0,11032	-2,53855	0,013047	-0,49955	-0,06055
Y_{t-2}	-0,11428	0,108183	-1,05632	0,293963	-0,32952	0,100974

Thus, the equation for forecasting demand for group B2 is:

$$\hat{Y}_t = 8{,}647759 + 1{,}312238 * J2 + 1{,}556617 * J3 + 1{,}598894 * J4 + 1{,}471431 * J5 + 1{,}596597 * J6 + 1{,}292789 * J7 + 1{,}289157 * J8 + 1{,}27563 * J9 + 2{,}073457 * J10 + 1{,}848825 * J11 + 0{,}76686 * J12 - 0{,}28005 * Y_{t-1} - 0{,}11428 * Y_{t-2}$$

Using the above equation, the values of estimated demand for the forecasting sample (35 observations) were calculated. Figure 29 depicts the actual and forecasted demand. Furthermore, the MAPE was calculated and it was found to be 6,02% indicating a highly accurate forecasting performance.

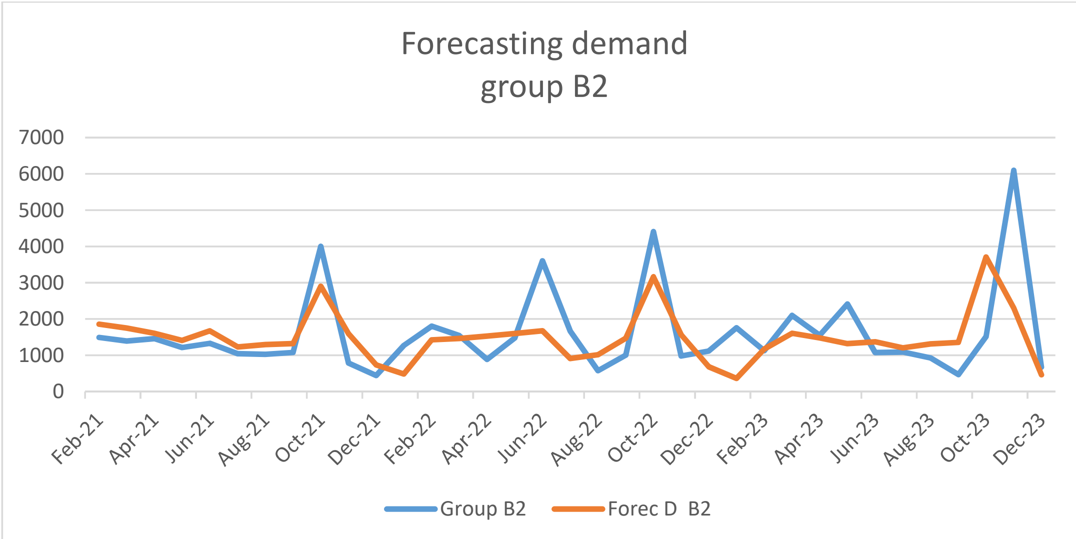

Figure 24 Time Plot ofactual and forecasting monthly demand for group B2

5. Conclusion and recommendations

Accurate forecasting of the demand for army spare parts is crucial, as it significantly enhances military readiness. As mentioned in Chapter 2, military expenses constitute a large percentage of each country's budget. Therefore, the efficient use of the national budget is a key goal for any government. Improving prediction accuracy requires constant effort, the use of historical data, and suitable forecasting techniques.

In this thesis, demand data for spare parts of military transportation vehicles, divided into four categories over a ten-year period, was used. Considering the steps of the present research, it was aimed to identify the main components of demand, such as trend, seasonality, and noise, and to investigate which time series analysis technique performs best in this study.

The results of the descriptive analysis and the outcomes of the regression analysis, combined with the time plots and box plots, confirm an overall upward trend for groups A1, B1, and A2. The positive values of the linear trend coefficient indicate an increasing trend in demand, and the very low p-values verify statistical significance at the 0.05 level. This characteristic does not exist in the dataset for B2 spare parts in all regression analyses.

Regarding the seasonality component of the time series analysis, the demand for spare parts changes over the months. The graphs illustrate a clear cyclical increase in specific months, such as June and October, for all groups. This observation is affirmed by dummy variables according to the regression analysis outputs. It is worth mentioning that the independent coefficient j12 (December) is not statistically significant for any group apart from B2. Moreover, it was found that lag variables (Y_{t-1} and Y_{t-2}) do not contribute to the variation in monthly demand for groups B1 and A2 only.

At this point, the research findings will be interpreted based on organizational elements. The seasonality and increased demand for spare parts observed mainly in June and October can be attributed to planned military exercises occurring during September-October. Participating military units request spare parts for vehicle repair and maintenance prior to these exercises to enhance readiness and address any new breakdowns.

Regarding December, which was confirmed as statistically insignificant, it is known to be the last month of the year. In the army, this month typically sees a reduction in spare parts requests due to the end of the financial year, combined with the Christmas and New Year holidays.

The upward trend confirmed by the research findings indicates that, over time, transport vehicles require more maintenance and repair due to the end-of-life of spare parts and the vehicles themselves. A notable finding is the consistent demand for spare parts for wheeled vehicles and their engine systems. This can be attributed to the reliability of the engines and their maintenance framework provided by the manufacturers. Additionally, the recent introduction of wheeled vehicles into the army's transport fleet, compared to tracked vehicles, contributes to this trend.

Applying the technique of regression analysis, the independent variables were investigated that are statistically significant and influence the dependent variable for all groups of spare parts. By incorporating the most important variables and omitting the less significant ones for each estimated sample, the forecasting equations were developed. The values of the coefficients confirm that October is the month with the highest demand. This conclusion can assist the organization's decision-makers in allocating additional resources and placing orders promptly. Moreover, the positive sign in all coefficients, except for the lag variables in group B2, indicates an increasing demand. This element is essential in the army's safety stock policy. To sum up, the forecasting equations for each group, along with their respective MAPE values, confirm the seasonality and forecast future demand with high accuracy. Additionally, using graphs, the good fit of the forecasting model was illustrated.

In conclusion, the results of this research can be incorporated into the organization's overall decision-making process by its managers. The military can achieve a more efficient balance between spare parts costs and operational readiness. With the information provided, the military organisation can secure valuable resources, optimize the safety stock and maintenance program, and simultaneously increase the availability of the transport fleet.It is important to note that the actual spare parts demand data pertain to a period of peace, and the application of the proposed forecasting model may be unreliable during times of tension, crisis, and war.

5.1 Future research

The present research study focuses on comparing the demand for spare parts in the drive system and engine operation of tracked and wheeled military transport vehicles. The actual demand data covers a period of ten years. To study and derive useful conclusions, time series techniques incorporating independent variables such as dummy and lag variables were used.

The proposed future demand forecasting model is applicable only to specific types of spare parts with particular characteristics, such as high procurement cost, limited lifespan, and critical importance to the operational readiness of the weapon system. Additionally, future research could examine common spare parts, such as light bulbs, maintenance oils, filters, etc.

Introducing additional variables into the model, such as procurement and inventory maintenance costs, military expenditures as a percentage of GDP, and the personnel involved in inventory management and vehicle maintenance and repair, also holds research interest.

If the military organisation aims to predict future demand for spare parts by considering even more factors and viewing demand as a complex system, the application of system dynamics(Sterman, 2000)and neural network models(Thomaidis, 2012)is recommended for future research.

5.2 Conclusion

The present survey of forecasting demand for spare parts for transport vehicles could be a useful tool for managers and senior officers of the military organization, taking into account its specificities and context of activities. The provided conclusions can contribute to the management of demand variability and the optimization of the safety stock. Accurately predicting future demand for spare parts, especially for a country's armed forces, is a critical factor in increasing operational readiness.

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Appendix A: Outputs of time series analysis

Table 1 Forecasting Errors using SMA (3) SMA(6) and SMA(12) for Group A1 and B1

	Group A1						Group B1					
Month	SMA(3)		SMA(6)		SMA(12)		SMA(3)		SMA(6)		SMA(12)	
Apr-13	-20	0,04					-71	0,03				
May-13	-555	4,63					-1256	0,67				
Jun-13	607	0,48					-272	0,12				
Jul-13	-348	1,24	-301	1,07			2555	0,53	2397	0,50		
Aug-13	8	0,01	-54	0,10			-717	0,31	-778	0,34		
Sep-13	-122	0,21	-96	0,17			-561	0,22	-302	0,12		
Oct-13	7907	0,94	7829	0,93			8088	0,72	8580	0,76		
Nov-13	-3154	185,55	-1844	108,49			-3863	2,53	-2669	1,75		
Dec-13	-2916	38,88	-1769	23,59			-4332	5,40	-3334	4,15		
Jan-14	-2715	24,91	-1539	14,12	-1006	9,23	-3909	6,16	-3245	5,11	-2499	3,93
Feb-14	323	0,83	-1229	3,15	-726	1,86	1220	0,55	-980	0,44	-916	0,42
Mar-14	145	0,43	-1255	3,74	-795	2,37	398	0,25	-1562	0,97	-1415	0,88
Apr-14	-104	0,60	-1377	7,91	-877	5,04	36	0,02	-1494	0,98	-1348	0,89
May-14	-53	0,21	64	0,26	-775	3,14	528	0,23	925	0,40	-480	0,21
Jun-14	1641	0,87	1671	0,88	860	0,45	1281	0,41	1580	0,51	269	0,09
Jul-14	-214	0,38	32	0,06	-529	0,95	-625	0,37	-214	0,13	-1205	0,72
Aug-14	-726	4,20	-427	2,47	-936	5,41	-112	0,05	179	0,08	-380	0,17
Sep-14	-657	3,03	-346	1,60	-860	3,96	-708	0,43	-444	0,27	-992	0,61
Oct-14	9420	0,97	9193	0,94	8689	0,89	12336	0,87	12110	0,85	11644	0,82
Nov-14	-2682	3,87	-1444	2,08	-467	0,67	-3054	1,03	-1222	0,41	183	0,06
Dec-14	-3252	10,95	-1915	6,45	-920	3,10	-4698	3,00	-2737	1,75	-1342	0,86
Jan-15	-3459	29,82	-1830	15,77	-1119	9,65	-5779	12,43	-3585	7,71	-2508	5,39
Feb-15	1163	0,76	-340	0,22	296	0,19	1387	0,45	-792	0,26	96	0,03
Mar-15	-217	0,50	-1668	3,87	-900	2,09	1105	0,39	-1180	0,42	-229	0,08
Apr-15	-562	4,29	-2003	15,29	-1208	9,22	-228	0,12	-2297	1,22	-1250	0,67
May-15	-501	2,54	-336	1,71	-1138	5,78	-672	0,35	-217	0,11	-1253	0,66
Jun-15	81	0,24	-117	0,35	-997	2,99	-203	0,10	46	0,02	-1133	0,57
Jul-15	1091	0,83	855	0,65	111	0,08	-334	0,21	-424	0,27	-1441	0,91
Aug-15	-427	2,29	-469	2,51	-1077	5,76	-659	0,56	-1033	0,88	-1855	1,58
Sep-15	-303	0,98	-124	0,40	-957	3,11	1629	0,51	1324	0,41	278	0,09
Oct-15	4947	0,89	5138	0,93	4276	0,77	10163	0,84	10196	0,84	9088	0,75
Nov-15	-1800	8,37	-1100	5,11	-709	3,30	-3121	1,30	-1280	0,53	-506	0,21
Dec-15	-1778	7,23	-1072	4,36	-638	2,59	-4895	4,78	-2728	2,66	-1824	1,78
Jan-16	511	0,20	1211	0,48	1634	0,65	-4639	8,40	-3040	5,51	-2252	4,08
Feb-16	-305	0,44	-816	1,19	-393	0,57	25	0,02	-2070	1,54	-1463	1,09
Mar-16	4989	0,81	4552	0,74	5129	0,84	1692	0,63	-781	0,29	-2	0,00

Apr-16	-2802	9,01	-2247	7,23	-1174	3,77	2851	0,65	1017	0,23	1715	0,39
May-16	-1831	3,34	-1137	2,08	-952	1,74	-223	0,09	514	0,20	-293	0,11
Jun-16	-1807	3,44	-1216	2,32	-1004	1,91	-1123	0,54	-9	0,00	-840	0,40
Jul-16	1622	0,78	296	0,14	538	0,26	-479	0,19	264	0,10	-399	0,16
Aug-16	-207	0,24	-870	1,03	-764	0,90	-1027	0,75	-1227	0,90	-1639	1,20
Sep-16	4755	0,81	4164	0,71	4242	0,72	215	0,10	-391	0,18	-815	0,37
Oct-16	2733	0,48	3975	0,70	3547	0,62	8463	0,81	7976	0,76	7559	0,72
Nov-16	1711	0,29	3257	0,56	3713	0,63	-2814	1,50	-1666	0,89	-924	0,49
Dec-16	-5467	15,80	-3136	9,06	-2265	6,55	-2705	1,25	-1271	0,59	-602	0,28
Jan-17	-2046	1,07	-1539	0,80	-707	0,37	-4006	4,78	-2602	3,10	-2015	2,40
Feb-17	7412	0,73	6692	0,66	7547	0,75	207	0,11	-1327	0,72	-1045	0,57
Mar-17	8562	0,67	7718	0,61	9332	0,74	1598	0,50	-29	0,01	289	0,09
Apr-17	11647	0,59	13787	0,69	15985	0,80	1678	0,46	235	0,06	674	0,19
May-17	1572	0,10	7335	0,46	10270	0,65	768	0,21	1402	0,38	759	0,21
Jun-17	-1208	0,08	4792	0,32	8114	0,54	-1028	0,42	-82	0,03	-519	0,21
Jul-17	-2701	0,19	1614	0,11	6164	0,44	-1897	1,40	-1248	0,92	-1664	1,22
Aug-17	-6145	0,70	-5779	0,66	-193	0,02	-750	0,43	-947	0,54	-1179	0,67
Sep-17	-4852	0,62	-6597	0,85	-1892	0,24	-110	0,06	-931	0,53	-1208	0,69
Oct-17	-444	0,05	-3751	0,38	-19	0,00	-116	0,08	-935	0,62	-1417	0,94
Nov-17	-887	0,11	-3967	0,50	-2259	0,29	7212	0,81	6797	0,77	6709	0,76
Dec-17	-6004	2,40	-8069	3,23	-7848	3,14	-3243	4,05	-2151	2,69	-1953	2,44
Jan-18	-6644	67,80	-8401	85,72	-10428	106,41	-3111	5,05	-2057	3,34	-2024	3,29
Feb-18	7980	0,69	5330	0,46	1109	0,10	1548	0,31	2430	0,49	2358	0,47
Mar-18	22610	0,83	20706	0,76	16815	0,62	4232	0,67	3277	0,51	3480	0,55
Apr-18	-12334	19,64	-9224	14,69	-11079	17,64	-1430	0,56	-1301	0,51	-591	0,23
May-18	1124	0,08	5942	0,42	4161	0,29	-1267	0,38	-666	0,20	309	0,09
Jun-18	-9900	2,38	-5214	1,25	-5809	1,39	-1664	0,68	-683	0,28	-601	0,25
Jul-18	10228	0,62	6923	0,42	7502	0,45	-312	0,13	-913	0,37	-557	0,23
Aug-18	-7997	2,18	-8732	2,38	-5607	1,53	-825	0,43	-1764	0,91	-1191	0,62
Sep-18	-1875	0,30	-4838	0,77	-2586	0,41	-671	0,42	-1580	0,98	-1530	0,95
Oct-18	-4901	1,24	-3657	0,93	-4786	1,22	1132	0,36	741	0,24	10	0,00
Nov-18	4656	0,50	1134	0,12	1047	0,11	5865	0,73	5599	0,69	4828	0,60
Dec-18	-2375	0,58	-3198	0,78	-4229	1,03	-3411	3,94	-2412	2,78	-2330	2,69
Jan-19	-5352	12,53	-6882	16,12	-8056	18,87	-3002	2,92	-1989	1,93	-2173	2,11
Feb-19	5590	0,55	5582	0,55	1689	0,17	-170	0,05	382	0,12	-77	0,02
Mar-19	11015	0,69	10225	0,64	7527	0,47	627	0,27	-670	0,29	-773	0,33
Apr-19	10908	0,55	12444	0,63	12305	0,62	796	0,27	-136	0,05	216	0,07
May-19	-9320	1,56	-3977	0,67	-3074	0,51	-154	0,06	-413	0,16	-124	0,05
Jun-19	-10595	3,22	-6108	1,85	-5065	1,54	-487	0,23	-8	0,00	-565	0,26
Jul-19	2085	0,18	2498	0,21	3475	0,30	1910	0,42	2123	0,47	1803	0,40
Aug-19	4345	0,38	203	0,02	3471	0,31	1567	0,34	1714	0,37	1804	0,39
Sep-19	13870	0,61	11328	0,50	14149	0,62	-593	0,19	-27	0,01	88	0,03
Oct-19	-108	0,01	2686	0,18	5263	0,35	377	0,08	1140	0,25	1269	0,28

Nov-19	-4175	0,34	517	0,04	1392	0,11	4986	0,55	5492	0,60	5762	0,63
Dec-19	-15356	11,57	-11417	8,60	-9746	7,34	-3538	1,72	-2630	1,28	-1369	0,67
Jan-20	-6460	2,08	-9308	2,99	-7732	2,49	-3801	2,68	-3252	2,30	-2107	1,49
Feb-20	1414	0,20	-4008	0,58	-4098	0,59	-1352	0,48	-1315	0,46	-717	0,25
Mar-20	15313	0,80	8871	0,46	8319	0,44	945	0,31	-800	0,26	-481	0,16
Apr-20	-717	0,08	-636	0,07	-2047	0,23	1482	0,38	90	0,02	326	0,08
May-20	620	0,05	3693	0,30	2153	0,17	984	0,23	523	0,12	582	0,14
Jun-20	8150	0,38	12991	0,60	10939	0,51	6612	0,64	7430	0,72	6548	0,63
Jul-20	4863	0,25	7159	0,37	6963	0,36	-2331	0,61	-462	0,12	-644	0,17
Aug-20	-3941	0,29	-935	0,07	930	0,07	-2171	0,55	-731	0,18	-454	0,11
Sep-20	-14186	3,54	-11830	2,95	-9032	2,25	-3827	1,72	-2668	1,20	-2143	0,96
Oct-20	949	0,07	-51	0,00	1785	0,13	5527	0,62	4116	0,46	4583	0,52
Nov-20	-2717	0,36	-6398	0,84	-3695	0,48	-2492	0,98	-3052	1,20	-2123	0,84
Dec-20	-5647	2,13	-10593	3,99	-8289	3,12	-2707	1,47	-3461	1,88	-2271	1,23
Jan-21	4741	0,38	2507	0,20	1538	0,12	-2570	1,39	-2036	1,10	-2246	1,22
Feb-21	12993	0,63	11632	0,56	8774	0,43	689	0,25	-788	0,28	-1366	0,49
Mar-21	10887	0,48	12713	0,56	9859	0,43	713	0,25	-485	0,17	-1260	0,44
Apr-21	-11262	1,52	-5846	0,79	-5871	0,79	3124	0,56	2161	0,38	1508	0,27
May-21	-11302	2,00	-6635	1,17	-7502	1,33	-1678	0,81	-842	0,41	-2180	1,05
Jun-21	-2176	0,22	-2167	0,22	-2808	0,29	317	0,08	1000	0,26	-234	0,06
Jul-21	-4701	1,61	-10230	3,50	-8695	2,97	-983	0,34	-309	0,11	-668	0,23
Aug-21	-2293	0,60	-7710	2,01	-6432	1,68	-573	0,24	-987	0,42	-1096	0,47
Sep-21	5853	0,51	2625	0,23	1934	0,17	-321	0,12	-573	0,21	-615	0,23
Oct-21	3968	0,40	3177	0,32	-39	0,00	5481	0,68	4877	0,60	4768	0,59
Nov-21	-4697	1,27	-3558	0,96	-6071	1,64	-918	0,26	-186	0,05	184	0,05
Dec-21	-534	0,07	888	0,11	-1623	0,21	-2261	0,91	-1389	0,56	-863	0,35
Jan-22	13159	0,65	13729	0,67	10459	0,51	70	0,01	1100	0,23	1348	0,28
Feb-22	13992	0,57	15102	0,61	14089	0,57	474	0,12	70	0,02	392	0,10
Mar-22	-7183	0,69	-2567	0,25	-450	0,04	455	0,11	-39	0,01	460	0,11
Apr-22	-10053	1,20	-4415	0,53	-1422	0,17	-1810	0,71	-1983	0,78	-1342	0,53
May-22	-13752	18,86	-11826	16,22	-9182	12,60	-305	0,09	-291	0,09	-322	0,10
Jun-22	4210	0,39	-1331	0,12	1227	0,11	1474	0,31	1265	0,26	1103	0,23
Jul-22	-2330	0,54	-8249	1,92	-5287	1,23	-384	0,12	-780	0,25	-636	0,20
Aug-22	1180	0,18	-3436	0,53	-3262	0,51	-1828	0,94	-1748	0,90	-1895	0,98
Sep-22	-5337	2,95	-5021	2,77	-8095	4,47	-1498	0,83	-1519	0,84	-1985	1,10
Oct-22	4630	0,53	3408	0,39	-304	0,03	7182	0,76	6559	0,69	5764	0,61
Nov-22	21167	0,79	21384	0,80	17840	0,66	-2239	1,03	-1915	0,88	-1665	0,77
Dec-22	-7841	1,69	-5170	1,11	-6290	1,35	-953	0,27	-363	0,10	-193	0,05
Jan-23	-8825	1,91	-4196	0,91	-6063	1,32	-1405	0,38	-25	0,01	-157	0,04
Feb-23	17305	0,59	20482	0,70	19979	0,68	-774	0,33	-1418	0,60	-1376	0,59
Mar-23	5927	0,32	6116	0,33	9038	0,48	2762	0,46	2108	0,35	2361	0,40
Apr-23	-916	0,05	1158	0,07	6212	0,37	-488	0,14	-1029	0,29	-231	0,07
May-23	-9751	0,82	-4969	0,42	707	0,06	316	0,07	720	0,17	439	0,10

Jun-23	2544	0,14	3996	0,22	6245	0,34	-1165	0,34	-475	0,14	-489	0,14
Jul-23	-15366	62,97	-16352	67,02	-12457	51,05	71	0,02	-65	0,02	17	0,00
Aug-23	-7519	2,87	-13251	5,06	-9747	3,72	-564	0,17	-624	0,19	-573	0,18
Sep-23	-5321	3,06	-9677	5,57	-10309	5,93	-1817	1,10	-2361	1,42	-2269	1,37
Oct-23	7880	0,84	842	0,09	-2627	0,28	423	0,13	15	0,00	-596	0,18
Nov-23	6741	0,59	3968	0,35	-760	0,07	5832	0,68	5298	0,62	5172	0,60
Dec-23	-555	0,08	-338	0,05	-3859	0,56	-3487	3,38	-2966	2,88	-2904	2,82
MAPE		3,376		3,330		3,168		0,946		0,758		0,673
		337,64%		333,00%		316,82%		94,56%		75,76%		67,34%

Table 2 Forecasting Errors using SMA (3) SMA(6) and SMA(12) for Group A2 and B2

	Group A2						Group B2					
Month	SMA(3)		SMA(6)		SMA(12)		SMA(3)		SMA(6)		SMA(12)	
Apr-13	2306	0,82					72	0,05				
May-13	-1196	11,61					-709	0,71				
Jun-13	-641	1,03					97	0,06				
Jul-13	-780	1,98	-439	1,11			140	0,09	92	0,06		
Aug-13	739	0,66	276	0,25			733	0,34	594	0,27		
Sep-13	-158	0,29	-436	0,79			169	0,09	271	0,14		
Oct-13	3162	0,82	2918	0,76			2684	0,58	2919	0,64		
Nov-13	-1686	11,09	-954	6,28			-2103	2,60	-1361	1,68		
Dec-13	-1255	4,77	-852	3,24			-1813	2,80	-1490	2,30		
Jan-14	-1200	5,43	-833	3,77	-723	3,27	-1700	5,40	-1646	5,22	-1408	4,47
Feb-14	464	0,69	-349	0,52	-255	0,38	1708	0,74	548	0,24	640	0,28
Mar-14	282	0,42	-283	0,42	-301	0,45	-37	0,03	-724	0,69	-693	0,66
Apr-14	-336	1,81	-786	4,22	-765	4,12	-397	0,48	-794	0,96	-821	1,00
May-14	-189	0,59	-40	0,13	-413	1,29	-211	0,18	190	0,16	-400	0,34
Jun-14	248	0,39	251	0,39	-112	0,17	159	0,14	125	0,11	-418	0,35
Jul-14	-62	0,19	-132	0,41	-433	1,35	60	0,05	-21	0,02	-431	0,38
Aug-14	-24	0,06	-66	0,16	-344	0,85	325	0,22	209	0,14	-29	0,02
Sep-14	1386	0,75	1417	0,77	1152	0,63	-666	1,12	-545	0,92	-862	1,45
Oct-14	6682	0,89	6918	0,92	6741	0,89	5819	0,85	5822	0,85	5544	0,81
Nov-14	-2761	5,53	-1344	2,69	-603	1,21	-1231	0,70	-316	0,18	225	0,13
Dec-14	1465	0,31	2884	0,61	3626	0,76	-2535	4,66	-1626	2,99	-1067	1,96
Jan-15	-4252	354,33	-2547	212,26	-1494	124,47	-2823	11,81	-1825	7,64	-1363	5,70
Feb-15	-887	1,02	-1639	1,89	-619	0,71	1498	0,64	428	0,18	749	0,32
Mar-15	-1153	1,59	-1860	2,56	-778	1,07	1725	0,62	707	0,26	1168	0,42
Apr-15	-314	1,41	-2178	9,81	-1287	5,80	-766	0,75	-1405	1,38	-725	0,71
May-15	-402	1,97	-977	4,79	-1308	6,41	-1203	1,43	-604	0,72	-918	1,09
Jun-15	196	0,34	-552	0,95	-922	1,59	-222	0,17	28	0,02	-411	0,31
Jul-15	118	0,26	18	0,04	-1044	2,31	-61	0,06	-423	0,42	-744	0,74
Aug-15	-281	2,15	-378	2,89	-1377	10,51	-610	1,38	-1106	2,50	-1290	2,91

Sep-15	1053	0,73	1055	0,73	-45	0,03	1407	0,60	1097	0,47	682	0,29
Oct-15	1984	0,75	2154	0,81	1207	0,45	2796	0,69	2895	0,71	2262	0,56
Nov-15	1076	0,43	1575	0,63	1440	0,58	-1028	0,82	-417	0,33	-308	0,25
Dec-15	-2062	15,51	-1159	8,71	-1079	8,11	-1521	1,49	-710	0,69	-490	0,48
Jan-16	-1678	20,72	-1136	14,03	-745	9,20	-1758	5,04	-1333	3,82	-1203	3,45
Feb-16	482	0,35	227	0,16	550	0,40	676	0,44	-25	0,02	-12	0,01
Mar-16	174	0,25	-658	0,93	-169	0,24	1074	0,52	289	0,14	552	0,27
Apr-16	310	0,30	-208	0,20	160	0,15	1291	0,50	895	0,34	1171	0,45
May-16	-873	5,23	-803	4,81	-774	4,63	-925	0,81	-328	0,29	-425	0,37
Jun-16	-138	0,28	-87	0,17	-441	0,89	-479	0,33	1	0,00	-139	0,10
Jul-16	-371	1,90	-449	2,30	-736	3,77	-813	0,88	-603	0,66	-682	0,74
Aug-16	689	0,71	312	0,32	66	0,07	-18	0,02	-466	0,40	-443	0,38
Sep-16	682	0,55	643	0,52	258	0,21	480	0,29	102	0,06	0	0,00
Oct-16	4370	0,84	4489	0,87	4210	0,81	2887	0,70	2642	0,64	2531	0,61
Nov-16	-1392	1,30	-304	0,28	-102	0,10	-1536	1,97	-965	1,24	-828	1,06
Dec-16	-1847	2,85	-878	1,36	-407	0,63	-1294	1,45	-788	0,88	-673	0,75
Jan-17	-2276	108,37	-1529	72,79	-1076	51,24	-1517	3,64	-1172	2,81	-1140	2,73
Feb-17	-177	0,44	-1119	2,78	-690	1,72	588	0,46	-221	0,17	-278	0,22
Mar-17	571	0,62	-497	0,54	-82	0,09	507	0,37	-155	0,11	-168	0,12
Apr-17	394	0,47	-530	0,63	-185	0,22	188	0,15	-267	0,22	-272	0,22
May-17	-290	0,67	-217	0,50	-578	1,33	1276	0,50	1572	0,61	1197	0,47
Jun-17	369	0,33	559	0,51	70	0,06	-324	0,23	101	0,07	-94	0,07
Jul-17	-81	0,11	92	0,13	-372	0,52	-970	1,29	-621	0,82	-728	0,97
Aug-17	-206	0,38	-193	0,35	-584	1,07	-582	0,59	-442	0,45	-479	0,49
Sep-17	33	0,04	59	0,07	-273	0,33	145	0,12	-191	0,16	-265	0,22
Oct-17	-352	1,03	-403	1,18	-718	2,10	-48	0,05	-421	0,45	-486	0,52
Nov-17	4666	0,89	4575	0,87	4579	0,87	1725	0,62	1457	0,53	1612	0,58
Dec-17	-1822	5,88	-1150	3,71	-693	2,24	-1000	1,60	-709	1,13	-687	1,10
Jan-18	-1624	4,80	-990	2,93	-637	1,88	-1155	4,08	-925	3,27	-1008	3,56
Feb-18	-1503	3,28	-807	1,76	-544	1,19	2336	0,66	2430	0,68	2280	0,64
Mar-18	3098	0,89	2217	0,64	2461	0,71	1378	0,48	1309	0,46	1398	0,49
Apr-18	-30	0,02	-301	0,22	173	0,12	-782	0,54	-383	0,26	-140	0,10
May-18	-804	0,83	-899	0,93	-295	0,31	-438	0,20	264	0,12	575	0,26
Jun-18	-923	0,91	-136	0,13	-289	0,28	-653	0,43	-313	0,21	-65	0,04
Jul-18	-158	0,16	-306	0,32	-333	0,34	-746	0,77	-1004	1,03	-619	0,64
Aug-18	-159	0,19	-553	0,67	-496	0,60	-250	0,19	-783	0,60	-301	0,23
Sep-18	-571	1,55	-1073	2,92	-978	2,67	-96	0,08	-548	0,47	-467	0,40
Oct-18	238	0,25	35	0,04	-349	0,36	118	0,09	-166	0,13	-367	0,29
Nov-18	4470	0,86	4336	0,84	3828	0,74	3653	0,74	3498	0,71	3238	0,66
Dec-18	-2119	40,74	-1502	28,89	-1303	25,05	-2219	9,69	-1629	7,11	-1615	7,05
Jan-19	-1384	2,03	-711	1,04	-651	0,95	-1271	1,47	-780	0,90	-948	1,10
Feb-19	-974	0,97	-345	0,35	-362	0,36	-8	0,00	366	0,18	131	0,07
Mar-19	296	0,34	-500	0,57	-533	0,61	-139	0,16	-850	0,96	-840	0,95

Apr-19	651	0,43	44	0,03	312	0,21	1906	0,60	1463	0,46	1590	0,50
May-19	119	0,10	-305	0,24	45	0,04	-927	0,86	-921	0,85	-622	0,57
Jun-19	-306	0,34	8	0,01	-322	0,36	-582	0,52	-242	0,21	-487	0,43
Jul-19	3011	0,71	3193	0,76	3013	0,71	17	0,01	287	0,16	224	0,12
Aug-19	-463	0,28	36	0,02	176	0,11	634	0,32	298	0,15	323	0,16
Sep-19	-1702	3,03	-1174	2,09	-994	1,77	-729	0,81	-766	0,85	-799	0,88
Oct-19	673	0,24	1140	0,40	1252	0,44	-442	0,40	-556	0,50	-564	0,50
Nov-19	5680	0,77	5459	0,74	5636	0,77	4414	0,77	4411	0,77	4077	0,71
Dec-19	-3058	5,84	-2399	4,58	-1384	2,64	-1916	2,84	-1438	2,13	-1066	1,58
Jan-20	-3131	7,13	-2421	5,51	-1508	3,43	-1909	3,16	-1433	2,37	-1173	1,94
Feb-20	-2365	5,77	-1818	4,43	-1517	3,70	-1161	0,98	-657	0,56	-575	0,49
Mar-20	499	0,52	-1063	1,11	-921	0,96	334	0,29	-552	0,48	-535	0,46
Apr-20	-33	0,06	-1517	2,67	-1315	2,31	362	0,27	-405	0,30	-369	0,28
May-20	1993	0,76	928	0,35	831	0,32	605	0,33	47	0,03	271	0,15
Jun-20	3622	0,72	4087	0,82	3087	0,62	3534	0,71	3845	0,77	3354	0,67
Jul-20	-1875	2,17	-807	0,93	-1401	1,62	-1300	0,92	-432	0,31	-527	0,37
Aug-20	-1002	0,55	94	0,05	-150	0,08	-1439	1,11	-681	0,52	-608	0,47
Sep-20	-1918	2,94	-1327	2,04	-1347	2,07	-1576	1,59	-1015	1,03	-866	0,88
Oct-20	7487	0,87	6676	0,78	6597	0,77	3200	0,72	2460	0,55	2575	0,58
Nov-20	-3134	5,57	-2704	4,80	-1926	3,42	-1425	1,75	-1675	2,05	-1321	1,62
Dec-20	-2641	4,18	-2289	3,62	-1290	2,04	-1433	2,21	-1675	2,59	-1079	1,67
Jan-21	-3024	12,50	-1950	8,06	-1689	6,98	-1543	3,65	-1177	2,78	-1301	3,08
Feb-21	1404	0,75	-205	0,11	-32	0,02	865	0,58	59	0,04	-215	0,14
Mar-21	708	0,44	-469	0,29	-410	0,25	538	0,39	-74	0,05	-342	0,25
Apr-21	-739	1,44	-1747	3,41	-1581	3,09	354	0,24	-78	0,05	-298	0,20
May-21	-750	1,27	-319	0,54	-1498	2,53	-234	0,19	176	0,14	-551	0,45
Jun-21	75	0,08	71	0,07	-933	0,95	-24	0,02	226	0,17	-382	0,29
Jul-21	277	0,28	0	0,00	-610	0,63	-292	0,28	-177	0,17	-368	0,35
Aug-21	-285	0,50	-530	0,94	-1027	1,82	-170	0,17	-296	0,29	-352	0,34
Sep-21	367	0,30	333	0,28	-278	0,23	-55	0,05	-166	0,15	-278	0,26
Oct-21	6825	0,88	6934	0,90	6208	0,80	2955	0,74	2813	0,70	2641	0,66
Nov-21	-2976	15,26	-1815	9,31	-1265	6,49	-1250	1,59	-830	1,06	-541	0,69
Dec-21	-2949	29,78	-1845	18,64	-1330	13,44	-1515	3,44	-1104	2,50	-884	2,00
Jan-22	-2080	3,48	-1199	2,00	-787	1,32	-470	0,37	-122	0,10	-33	0,03
Feb-22	471	0,61	-966	1,26	-647	0,84	969	0,54	368	0,20	425	0,24
Mar-22	50	0,09	-1230	2,29	-784	1,46	370	0,24	-21	0,01	139	0,09
Apr-22	231	0,27	-790	0,91	-365	0,42	-652	0,73	-754	0,85	-529	0,60
May-22	-62	0,09	151	0,23	-599	0,90	70	0,05	359	0,24	112	0,08
Jun-22	2356	0,77	2457	0,81	1779	0,58	2299	0,64	2365	0,66	2212	0,61
Jul-22	596	0,28	1041	0,49	682	0,32	-320	0,19	-94	0,06	90	0,05
Aug-22	-1800	12,68	-1191	8,39	-1392	9,80	-1676	2,91	-1256	2,18	-1057	1,84
Sep-22	-1513	5,91	-973	3,80	-1242	4,85	-948	0,95	-625	0,62	-594	0,59
Oct-22	5286	0,86	4943	0,81	4706	0,77	3329	0,75	2875	0,65	2823	0,64

Nov-22	-1514	2,29	-1398	2,12	-625	0,95	-1016	1,04	-1143	1,17	-642	0,65
Dec-22	-2138	10,23	-1849	8,85	-1114	5,33	-1014	0,91	-923	0,83	-522	0,47
Jan-23	-1993	5,90	-1247	3,69	-994	2,94	-413	0,24	130	0,07	61	0,03
Feb-23	815	0,67	-71	0,06	-94	0,08	-156	0,14	-512	0,45	-607	0,54
Mar-23	1411	0,71	532	0,27	651	0,33	769	0,37	371	0,18	424	0,20
Apr-23	-129	0,12	-702	0,66	-414	0,39	-114	0,07	-368	0,24	-178	0,11
May-23	39	0,03	550	0,38	-23	0,02	820	0,34	974	0,40	632	0,26
Jun-23	230	0,13	689	0,40	184	0,11	-943	0,87	-600	0,56	-781	0,72
Jul-23	-1123	3,81	-1007	3,41	-1148	3,89	-592	0,54	-583	0,54	-560	0,51
Aug-23	-707	1,54	-836	1,83	-833	1,82	-600	0,65	-634	0,68	-674	0,73
Sep-23	-630	3,15	-968	4,84	-1118	5,59	-563	1,20	-1058	2,26	-1161	2,48
Oct-23	404	0,56	-146	0,20	-591	0,82	691	0,45	265	0,17	-67	0,04
Nov-23	5408	0,92	5056	0,86	5005	0,85	5126	0,84	4849	0,80	4753	0,78
Dec-23	-1433	1,73	-717	0,86	-467	0,56	-2022	3,00	-1191	1,77	-1098	1,63
MAPE		6,443		4,511		3,392		1,064		0,853		0,798
		644,3%		451,1%		339,20%		106,43%		85,30%		79,75%

Table 3 Summary outpout for group A1 and variables B1, A2 and B2

Regression Statistics	
Multiple R	0,738746
R Square	0,545746
Adjusted R Square	0,531439
Standard Error	1,183555
Observations	132

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	213,7337	53,43343	38,14486	6,17E-21
Residual	127	177,902	1,400803		
Total	131	391,6357			

	Coefficient	*Standard Error*	*t-stat*	*P-Value*	*Lower 95%*	*Upper 95%*
Intercept	-0,33671	1,368146	-0,2461	0,805999	-3,04402	2,370607
Month	0,024595	0,003094	7,948938	8,82E-13	0,018473	0,030718
LN B1	0,660118	0,334306	1,974596	0,050484	-0,00141	1,321649
LN A2	0,259809	0,139437	1,863276	0,064733	-0,01611	0,535729
LN B2	-0,03837	0,34372	-0,11162	0,9113	-0,71853	0,641794

Table 4 Summary outpout for group B1 and variables A1, A2 and B2

Regression Statistics	
Multiple R	0,882437
R Square	0,778696

Adjusted R Square	0,771726
Standard Error	0,30944
Observations	132

ANOVA

	df	SS	MS	F	Significance F
Regression	4	42,78931	10,69733	111,7177	1,29E-40
Residual	127	12,16065	0,095753		
Total	131	54,94996			

	Coefficient	Standard Error	t-stat	P-Value	Lower 95%	Upper 95%
Intercept	1,833189	0,318669	5,752645	6,21E-08	1,202601	2,463777
Month	0,00279	0,000958	2,911198	0,004254	0,000894	0,004687
LN A1	0,045123	0,022852	1,974596	0,050484	-9,7E-05	0,090343
LN A2	0,047633	0,036708	1,297607	0,196774	-0,02501	0,120271
LN B2	0,724424	0,062804	11,53459	1,69E-21	0,600145	0,848702

Table 5 Summary outpout for group A2 and variables A1, B1 and B2

Regression Statistics	
Multiple R	0,767695
R Square	0,589356
Adjusted R Square	0,576423
Standard Error	0,74311
Observations	132

ANOVA

	df	SS	MS	F	Significance F
Regression	4	100,6522	25,16306	45,56765	1,1E-23
Residual	127	70,13108	0,552213		
Total	131	170,7833			

	Coefficient	Standard Error	t-stat	P-Value	Lower 95%	Upper 95%
Intercept	-3,37053	0,805477	-4,18452	5,29E-05	-4,96443	-1,77664
Month	0,000753	0,002376	0,316745	0,751957	-0,00395	0,005455
LN A1	0,10242	0,054968	1,863276	0,064733	-0,00635	0,211191
LN B1	0,2747	0,211697	1,297607	0,196774	-0,14421	0,69361
LN B2	0,966419	0,198051	4,879655	3,12E-06	0,574513	1,358326

Table 6 Summary outpoutfor group B2 and variables A1, B1 and A2

Regression Statistics	
Multiple R	0,887784
R Square	0,788161
Adjusted R Square	0,781489

Standard Error	0,305535
Observations	132

ANOVA

	df	SS	MS	F	Significance F
Regression	4	44,10965	11,02741	118,1279	8,12E-42
Residual	127	11,85563	0,093351		
Total	131	55,96528			

	Coefficient	Standard Error	t-stat	P-Value	Lower 95%	Upper 95%
Intercept	0,789399	0,346257	2,279808	0,024287	0,104219	1,474578
Month	-0,00367	0,000922	-3,98494	0,000113	-0,0055	-0,00185
LN A1	-0,00256	0,022906	-0,11162	0,9113	-0,04788	0,04277
LN B1	0,706253	0,061229	11,53459	1,69E-21	0,585092	0,827415
LN A2	0,163373	0,03348	4,879655	3,12E-06	0,097121	0,229624

Table 7 Summary output with dummy and first order lag variables for group A1

Regression Statistics	
Multiple R	0,99037
R Square	0,980834
Adjusted R Square	0,970157
Standard Error	1,193378
Observations	131

ANOVA

	df	SS	MS	F	Significance F
Regression	14	8527,06	609,0757	427,6763	1E-92
Residual	117	166,6257	1,424151		
Total	131	8693,686			

	Coefficient	Standard Error	t-stat	P-Value	Lower 95%	Upper 95%
Constant term	3,691851	0,612093	6,031517	1,95E-08	2,479632	4,904069
linear trend	0,020273	0,003785	5,356639	4,3E-07	0,012777	0,027768
j2	1,379607	0,52162	2,644852	0,009295	0,346567	2,412648
j3	1,272949	0,53791	2,366474	0,019601	0,207647	2,338251
j4	0,137619	0,545702	0,252187	0,801339	-0,94312	1,218353
j5	0,312646	0,526059	0,594317	0,553447	-0,72919	1,354478
j6	0,98083	0,524586	1,869722	0,064022	-0,05809	2,019746
j7	0,406021	0,533457	0,761114	0,44812	-0,65046	1,462504
j8	0,253723	0,527321	0,481154	0,631306	-0,79061	1,298055
j9	0,485063	0,524339	0,925094	0,356821	-0,55336	1,523489
j10	1,596145	0,525928	3,034911	0,002966	0,554572	2,637719
j11	0,139886	0,548545	0,255012	0,799161	-0,94648	1,226251
j12	-0,35564	0,526591	-0,67537	0,500774	-1,39853	0,687243

Y_{t-1}	0,300213	0,088072	3,408724	0,000896	0,125791	0,474634

Table 8 Summary outpout with dummy, first order and second order lag variables for group A1

Regression Statistics	
Multiple R	0,991206
R Square	0,982489
Adjusted R Square	0,971662
Standard Error	1,148657
Observations	130

ANOVA

	df	SS	MS	F	Significance F
Regression	15	8513,464	567,5643	430,1646	8,45E-93
Residual	115	151,7324	1,319412		
Total	130	8665,196			

	Coefficient	Standard Error	t-stat	P-Value	Lower 95%	Upper 95%
Constant term	2,51409	0,708562	3,548159	0,000563	1,110565	3,917615
linear trend	0,0141	0,004091	3,44649	0,000794	0,005996	0,022203
j2	1,744732	0,519845	3,356252	0,001071	0,715019	2,774445
j3	1,638621	0,529918	3,092219	0,002493	0,588956	2,688286
j4	0,119349	0,525348	0,227181	0,820687	-0,92126	1,159961
j5	0,107865	0,510479	0,211302	0,833026	-0,9033	1,119026
j6	1,05919	0,505491	2,095368	0,038333	0,057909	2,06047
j7	0,579965	0,516187	1,123556	0,263541	-0,4425	1,602431
j8	0,214987	0,507754	0,423408	0,672789	-0,79078	1,220749
j9	0,532726	0,50489	1,055132	0,293576	-0,46736	1,532815
j10	1,734229	0,507957	3,414126	0,000885	0,728064	2,740394
j11	0,339452	0,531395	0,638793	0,524228	-0,71314	1,392043
j12	-0,58418	0,512135	-1,14067	0,256375	-1,59862	0,430261
Y_{t-1}	0,2104	0,088986	2,364414	0,019734	0,034136	0,386665
Y_{t-2}	0,284535	0,088922	3,199818	0,001778	0,108397	0,460673

Table 9 Summary outpout with dummy and first order lag variables for group B1

Regression Statistics	
Multiple R	0,998382
R Square	0,996766
Adjusted R Square	0,98786
Standard Error	0,476574
Observations	131

ANOVA

	df	SS	MS	F	Significance F

Regression	14	8191,148	585,082	2576,057	1,6E-137
Residual	117	26,5734	0,227123		
Total	131	8217,722			

	Coefficient	*Standard Error*	*t-stat*	*P-Value*	*Lower 95%*	*Upper 95%*
Constant term	7,082491	0,673843	10,5106	1,34E-18	5,747981	8,417001
linear trend	0,004687	0,001189	3,941676	0,000138	0,002332	0,007042
j2	0,879749	0,210101	4,18727	5,5E-05	0,463656	1,295843
j3	1,090534	0,215903	5,05103	1,63E-06	0,662949	1,518119
j4	1,0057	0,220509	4,560816	1,26E-05	0,568994	1,442406
j5	0,936206	0,217802	4,298427	3,58E-05	0,50486	1,367551
j6	1,027981	0,216089	4,757201	5,65E-06	0,600027	1,455934
j7	0,903454	0,218604	4,132832	6,76E-05	0,47052	1,336389
j8	0,698423	0,21525	3,244709	0,001533	0,272132	1,124714
j9	0,643236	0,211326	3,043811	0,002886	0,224716	1,061756
j10	1,747827	0,210654	8,297159	2,09E-13	1,330638	2,165016
j11	1,240124	0,248029	4,999908	2,04E-06	0,748915	1,731334
j12	0,263825	0,224055	1,177503	0,241384	-0,1799	0,707554
Y_{t-1}	-0,04735	0,09308	-0,50869	0,611928	-0,23169	0,136992

Table 10 Summary outpout with dummy, first order and second order lag variables for group B1

Regression Statistics	
Multiple R	0,998384
R Square	0,996771
Adjusted R Square	0,987682
Standard Error	0,478453
Observations	130

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	15	8125,423	541,6949	2366,337	1,3E-134
Residual	115	26,32546	0,228917		
Total	130	8151,749			

	Coefficient	*Standard Error*	*t-stat*	*P-Value*	*Lower 95%*	*Upper 95%*
Constant term	7,10916	1,01885	6,977635	2,04E-10	5,091015	9,127305
linear trend	0,004874	0,001282	3,802809	0,000231	0,002335	0,007413
j2	0,828317	0,229704	3,606018	0,000461	0,373317	1,283316
j3	1,083327	0,240518	4,504146	1,61E-05	0,606908	1,559746
j4	1,003377	0,222152	4,516631	1,53E-05	0,563337	1,443416
j5	0,93489	0,218684	4,275081	3,96E-05	0,50172	1,36806
j6	1,026071	0,217272	4,722525	6,63E-06	0,595697	1,456444
j7	0,900804	0,220188	4,091058	8E-05	0,464653	1,336955

j8	0,696417	0,2163	3,219675	0,001668	0,267967	1,124866
j9	0,640681	0,213301	3,003652	0,003274	0,218173	1,063188
j10	1,744009	0,215401	8,096572	6,6E-13	1,317341	2,170677
j11	1,233715	0,252508	4,885853	3,36E-06	0,733546	1,733884
j12	0,264906	0,232983	1,137017	0,257895	-0,19659	0,726401
Y_{t-1}	-0,04541	0,093522	-0,48551	0,628237	-0,23065	0,139843
Y_{t-2}	-0,00594	0,094086	-0,06311	0,949786	-0,1923	0,180428

Table 11 Summary outpout with dummy and first order lag variables for group A2

Regression Statistics	
Multiple R	0,990875
R Square	0,981834
Adjusted R Square	0,971269
Standard Error	0,954206
Observations	131

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	14	5757,771	411,2693	451,6914	4,5E-94
Residual	117	106,5296	0,91051		
Total	131	5864,3			

	Coefficient	*Standard Error*	*t-stat*	*P-Value*	*Lower 95%*	*Upper 95%*
Constant term	5,592871	0,599662	9,326714	8,4E-16	4,405273	6,780469
linear trend	0,006054	0,002254	2,68549	0,008295	0,00159	0,010519
j2	1,362598	0,41988	3,245209	0,001531	0,531048	2,194148
j3	1,934872	0,423422	4,569613	1,22E-05	1,096308	2,773437
j4	1,689212	0,430658	3,922396	0,000148	0,836316	2,542108
j5	1,263292	0,424614	2,975153	0,003558	0,422366	2,104217
j6	1,941863	0,419413	4,629948	9,54E-06	1,111236	2,772489
j7	1,573233	0,431849	3,643018	0,000403	0,717979	2,428487
j8	1,336188	0,422633	3,16158	0,001999	0,499185	2,17319
j9	1,43865	0,42043	3,421853	0,000858	0,60601	2,27129
j10	2,905205	0,422108	6,882607	3,1E-10	2,069242	3,741168
j11	2,316624	0,46146	5,020209	1,87E-06	1,402727	3,230521
j12	0,887762	0,435304	2,039406	0,043662	0,025665	1,749858
Y_{t-1}	-0,1466	0,091109	-1,60907	0,110296	-0,32704	0,033836

Table 12 Summary outpout with dummy, first order and second order lag variables for group A2

Regression Statistics	
Multiple R	0,990893
R Square	0,981869

Adjusted R Square	0,970967
Standard Error	0,95922
Observations	130

ANOVA

	df	SS	MS	F	Significance F
Regression	15	5730,311	382,0207	415,1932	6,11E-92
Residual	115	105,8119	0,920103		
Total	130	5836,123			

	Coefficient	Standard Error	t-stat	P-Value	Lower 95%	Upper 95%
Constant term	5,467591	0,930046	5,878837	4,12E-08	3,625348	7,309835
linear trend	0,005657	0,002347	2,410376	0,017521	0,001008	0,010306
j2	1,465111	0,450757	3,250337	0,001512	0,572249	2,357974
j3	1,950242	0,452953	4,305615	3,52E-05	1,053029	2,847455
j4	1,682345	0,433762	3,878497	0,000176	0,823146	2,541544
j5	1,254547	0,426991	2,938113	0,003991	0,408761	2,100333
j6	1,941509	0,4225	4,59529	1,11E-05	1,104618	2,7784
j7	1,570911	0,437347	3,591906	0,000484	0,70461	2,437212
j8	1,3288	0,425026	3,126397	0,002241	0,486905	2,170695
j9	1,439891	0,424266	3,393841	0,000946	0,599502	2,28028
j10	2,907739	0,427358	6,803989	4,84E-10	2,061225	3,754253
j11	2,302758	0,464603	4,956395	2,5E-06	1,382468	3,223047
j12	0,862228	0,450433	1,91422	0,058077	-0,02999	1,75445
Y_{t-1}	-0,13631	0,093195	-1,46264	0,146294	-0,32091	0,048291
Y_{t-2}	0,013936	0,093433	0,149152	0,881695	-0,17114	0,199009

Table 13 Summary outpout with dummy and first order lag variables for group B2

Regression Statistics	
Multiple R	0,99777
R Square	0,995545
Adjusted R Square	0,986503
Standard Error	0,508587
Observations	131

ANOVA

	df	SS	MS	F	Significance F
Regression	14	6762,549	483,0392	1867,46	1,9E-129
Residual	117	30,26335	0,258661		
Total	131	6792,812			

	Coefficient	Standard Error	t-stat	P-Value	Lower 95%	Upper 95%
Constant term	7,513107	0,603404	12,45121	3,55E-23	6,318097	8,708116
linear trend	0,000724	0,001179	0,61398	0,540421	-0,00161	0,00306

j2	1,160005	0,22255	5,212323	8,12E-07	0,719255	1,600754
j3	1,350583	0,239557	5,637848	1,21E-07	0,876154	1,825012
j4	1,204134	0,238413	5,050623	1,64E-06	0,731969	1,676298
j5	1,179067	0,234162	5,035269	1,75E-06	0,715322	1,642812
j6	1,31216	0,234247	5,601617	1,43E-07	0,848247	1,776073
j7	1,000898	0,238279	4,200531	5,22E-05	0,528999	1,472796
j8	0,872096	0,22909	3,806784	0,000226	0,418396	1,325797
j9	0,855624	0,227843	3,755321	0,000271	0,404393	1,306855
j10	1,788268	0,227779	7,850896	2,19E-12	1,337164	2,239372
j11	1,493484	0,259388	5,757717	7E-08	0,979779	2,007189
j12	0,392745	0,239957	1,63673	0,104374	-0,08248	0,867968
Y_{t-1}	-0,20188	0,089764	-2,24897	0,026386	-0,37965	-0,0241

Table 14 Summary outpout with dummy, first order and second order lag variables for group B2

Regression Statistics	
Multiple R	0,997833
R Square	0,99567
Adjusted R Square	0,986447
Standard Error	0,503815
Observations	130

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	15	6712,389	447,4926	1762,963	2,4E-127
Residual	115	29,19043	0,25383		
Total	130	6741,579			

	Coefficient	*Standard Error*	*t-stat*	*P-Value*	*Lower 95%*	*Upper 95%*
Constant term	9,153346	1,007778	9,082704	3,55E-15	7,157133	11,14956
linear trend	0,000698	0,001182	0,590799	0,555815	-0,00164	0,003039
j2	0,99504	0,241796	4,115208	7,3E-05	0,516089	1,47399
j3	1,195439	0,24905	4,799996	4,81E-06	0,702119	1,688759
j4	1,260714	0,238226	5,29209	5,86E-07	0,788834	1,732593
j5	1,224124	0,23332	5,246537	7,15E-07	0,761961	1,686286
j6	1,330832	0,232474	5,724642	8,4E-08	0,870345	1,791319
j7	1,025204	0,236664	4,3319	3,18E-05	0,556418	1,493989
j8	0,90943	0,227844	3,991469	0,000116	0,458116	1,360745
j9	0,826303	0,226202	3,652945	0,000392	0,378241	1,274365
j10	1,74738	0,226547	7,713092	4,85E-12	1,298634	2,196127
j11	1,486328	0,257487	5,772429	6,74E-08	0,976295	1,996361
j12	0,546334	0,249888	2,186318	0,030818	0,051355	1,041313
Y_{t-1}	-0,23871	0,091714	-2,6027	0,010467	-0,42037	-0,05704
Y_{t-2}	-0,19109	0,093495	-2,04381	0,043257	-0,37628	-0,00589

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