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An Application on Demand Forecasting and Stock Control For Aircraft Components

Emre EKİN[1]

[1] *Dr., Marmara Üniversitesi, Ekonometri Anabilim Dalı-Yöneylem Araştırması Bilim Dalı Doktora Mezunu, emrenike@hotmail.com*

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ORCID: 0000-0002-4043-9750

ABSTRACT

Today, the management of the inventory used in the aircraft maintenance-repair industry is an important issue. Spare parts inventory, in other words component inventory, constitutes the main capital resource of this type of companies. For this reason, it is an important and sensitive issue for organizations engaged in aircraft maintenance to effectively manage their spare parts stock. Effective and rational management of spare parts inventory will provide companies with significant cost advantages. While trying to increase service levels, companies aim to keep their inventory costs at minimum levels. In order to effectively manage the spare parts inventory, first of all, the demand forecast for the future must be made correctly. For this, techniques suitable for the part structure should be used. The next step after forecasting is to keep stock at a sufficient level of confidence to avoid running out of stock in the future. Because of this, demands are formulated by fitting distributions. In this study, component data of a local company that provides maintenance and spare parts services to the aircraft of airline companies in the aviation maintenance and repair sector was used. Demand patterns related to the data set were examined and discrete forecasting methods were applied to them. Afterwards, comparisons were made by using various distributions to determine the amount of spares that should be kept in stock. The results were interpreted and evaluated. It is assessed that this study will shed light on and benefit organizations operating in the aviation sector and other sectors in terms of spare part stock management and demand forecasting..

Keywords: Demand Forecasting, stock control management, forecasting methods, aircraft components, aviation industry.

Uçak Komponentleri için Talep Tahmini ve Stok Kontrolüne İlişkin Bir Uygulama

ÖZET

Günümüzde uçak bakım-onarım sektöründe kullanılan envanterin yönetimi önemli bir konudur. Yedek parça envanteri bir diğer deyişle component envanteri bu tip firmaların ana sermaye kaynağını oluşturmaktadır. Bu sebeple uçak bakımıyla uğraşan kuruluşların yedek parça stoğunu etkin bir şekilde yönetmesi önemli ve hassas bir konudur. Yedek parça envanterinin etkin ve rasyonel şekilde yönetilmesi şirketlere önemli maliyet avantajları sağlayacaktır. Firmalar bir yandan hizmet seviyelerini yükseltmeye çalışırken diğer yandan ise stok maliyetlerini minimum seviyelerde tutmayı hedeflerler. Yedek parça envanterinin efektif olarak yönetilebilmesi için öncelikle gelecekle ilgili talep tahmininin doğru yapılması gerekmektedir. Bunun için parça yapısına uygun teknikler kullanılmalıdır. Tahminden sonraki aşama ileride stoksuzlukla karşılaşmamak için yeterli güven seviyesinde elde stok bulundurmaktır. Bunun için talepler dağılımlara uydurularak formülize edilirler. Bu çalışmada, havacılık bakım onarım sektöründe havayolu firmalarının uçaklarına bakım ve yedek parça hizmeti sunan yerel bir firmaya ait komponent verileri kullanılmıştır. Veri setine ilişkin talep kalıpları incelenmiş ve onlara kesikli tahmin yöntemleri uygulanmıştır. Daha sonra stokta bulundurulması gereken yedek miktarlarını belirlemek için çeşitli dağılımlardan yararlanılarak kıyaslama yapılmıştır. Elde edilen sonuçlar yorumlanarak değerlendirme yapılmıştır. Bu çalışmanın havacılık sektöründe ve diğer sektörlerde faaliyet gösteren kuruluşlara yedek parça stok yönetimi ve talep tahmini açısından ışık tutacağı ve fayda sağlayacağı değerlendirilmektedir.

Anahtar Kelimeler: Talep tahmini, stok kontrol yönetimi, tahmin yöntemleri, uçak yedek parçaları, havacılık sektörü.

1. INTRODUCTION

Today, in many industries, it is important to manage spare parts inventory management in a rational, effective and scientific system. Some of these sectors are; military weapons systems, commercial aerospace, telecommunications and automotive. While some of the spare parts are made available to the end users, some are used in places such as manufacturing and maintenance facilities. The sector examined in the study is the aviation maintenance and repair sector. In this sector, the absence of some critical spare parts in stock when requested causes aircraft to stay on the ground and be delayed and unable to take off. This situation both increases costs and causes loss of prestige and customers. On the other hand, keeping a spare part in stock unnecessarily also creates additional inventory holding costs. As a result; It is obvious that keeping extra spare parts or missing spare parts is not rational, it is a negative situation in terms of the supply chain, and it has an effect that disrupts flight operations and increases costs.

Aircraft spare parts are mostly in discrete demand structure. It may be necessary to apply different methods for the stock management of these parts. In other words, part failures may not always come regularly, and there may also be imbalances and fluctuations in demands due to the change in the number of aircraft serving in the airline's fleet. Therefore, spare parts should be classified well, forecasted future failure numbers should be determined by appropriate methods, and spare levels should be calculated with stock control models in order for operations to run smoothly.

In the study, repairable aircraft spare parts, namely components, were examined. Since these parts have a closed cap, they should be analyzed separately from other consumables. The main issue in stock control is to be flexible enough against the demands (breakdowns) that may occur during the supply period of the part and to keep the demanded stock in the warehouse at that time. The study consists of four main parts. In the first part, literature-based information is given about demand patterns and their determination with certain classifications, and then the application of forecasting methods suitable for that pattern. In forecasting methods, methods suitable for discrete demand structure are explained. In the second part, the demand distributions researched in the literature on stock control are given. Matching demand to distribution is a key process in inventory control. In addition, the compatibility degrees of various distributions were tested, and which distributions yielded results in spare parts inventory control were examined. In the third part, a case study of forecasting and stock control is made with some failure data from an aviation maintenance and repair center. In the last part, conclusion, evaluation and future researches are given.

2. SPARE PARTS DEMAND STRUCTURES AND FORECAST METHODS

Categorization of the demand pattern is an important element in many inventory control software. In the software industry, demand patterns are classified arbitrarily and a forecasting procedure followed by a stock control method is determined. Thus, future needs are predicted and stock is managed effectively. For example, the demand is defined as slow, intermittent, lumpy or fast by giving certain limit values to the number of periods in which demand occurs in a year, the average demand or the standard deviation of the demand size (Syntetos, 2005). Classification of demand is of great importance in order to make precise and accurate forecasts. Demand classification; may be importance, the frequency or cost of parts, or a combination of these with another criterion. This means keeping critical and frequently used spare parts in stock. However, stocking up on junk and unnecessary parts will lead to undesirable costs. Therefore, it is essential to control the quantities of spare parts without stopping the flow in the production line (Hemeimat, 2016). Generally, when selecting appropriate forecasting methods as a result of examining demand data sets in fast moving parts, forecast parameters are optimized and the mean squared error (MSE) value is tried to be minimized. In other categories, moving averages, simple exponential weighted averages or Croston methods are preferred in forecasting procedures. Clustering procedures may be required in sparse and irregular demand patterns.

By categorizing again at certain time intervals, excessively deviating values are examined, it is checked whether the product categories have changed or not, and logical inconsistencies are discovered. Finally; The purpose of the classification exercise is to determine an estimation procedure to follow (Syntetos, 2005). Demand forecasting is one of the main aspects of inventory management. Forecasts form the basis of stock level planning. For example, a common problem in the airline industry is to forecast short-term demand with the highest possible accuracy. Due to the high cost of modern aircraft and repairable spare parts (avionics, aircraft engines, etc.), airline operators invest heavily. Even if these parts are in low demand, their absence can cause high downtime costs (Pham, 2006). For this reason, the methods used in estimating spare parts with discrete demand are discussed in the next sections. Theoretical comparisons of forecasting methods should be based on a measure of precision. Mean squared error (MSE) is the most easily traceable measure mathematically. By comparing the theoretical MSEs of the estimation methods, the superior method is found (Syntetos, 2005).

2.1. Information In the Literature On Spare Part Classification

Most of the articles in the literature deal with quantitative classifications. The most common technique is ABC analysis. Matrix models, which can be created according to the demand volume with a single criterion, are also used in multi-criteria classification with applications such as weighted linear optimization, artificial neural networks, weighted Euclidean distances, quadratic optimization and fuzzy logic. Unlike these, Syntetos and Boylan propose a demand-based classification. n this classification, demand variability (CV2) and order frequency are placed on a two-dimensional matrix. Williams and Eaves recommend dividing demand variability during the procurement process. While Yamashina suggested in-use product quantity curves and service part demand curves as inputs in spare parts classification, Nagarur et al., Poras and Dekker instead proposed hierarchical and two- or three-dimensional attribute-quantitative classification. Ernst and Cohen applied the Operations Related Groups methodology on 40 variables based on the clustering technique (Gani, 2017: 285).

Petrovic, on the other hand, proposed the expert system model, which combines failure rates with fuzzy logic (Bacchetti & Saccani, 2012). Vital, Essential, Desirable (VED) is a quantitative method taught to the inculcated by construction. It has been tackled with other systems as it is a difficult task to perform VED analysis. For instance, Gajpal et al. have done VED classification of spare parts using the AHP procedure (Bacchetti & Saccani, 2012).

2.2. Classification Of Spare Parts According To Demand Pattern

Fast-moving service parts are mostly estimated by time series methods. The specific method to be applied should be chosen in accordance with the characteristic of the demand pattern. For parts with non-discrete demand, exponential smoothing methods are often used. It is necessary to use other methods for parts that have discrete demand, that is, there is no demand in some periods (Boylan & Syntetos, 2008).

According to the definition of Silver, Pyke, and Peterson (1998), demand is said to be discrete or intermittent if the mean time sparsity between consecutive transactions is considerably higher than per unit time period. Unstable or unbalanced demand is the structure where mostly small demand transactions and occasional large demand transactions are seen. Discrete and unstable demand structures are common for spare parts. If a part is in both discrete and unstable demand structure, this structure is called a lumpy demand structure.

The obvious way to classify spare parts is by demand frequency. Dilution of the demand in certain periods or even being zero brings with it some problems. From the estimation perspective according to Croston, single exponential smoothing is not recommended under these circumstances. An integral method for classification is demand size variability. Syntetos et al. have identified two key categorization variables. These are the Average Demand Interval (ADI) and the Squared Coefficient of Variation (CV2) (Boylan J.E. & Syntetos A.A., 2008). Williams grouped demand patterns into four categories. These classification schemes have the following characteristics.

The condition ADI ≤ x, CV2 ≤ y indicates parts that are not very discrete and unstable. That is, they are spare parts in the category with fast movement and demand structures that do not cause difficulties in forecasting and stock control.

The condition ADI > x, CV2 ≤ y tests spare parts with low or intermittent demand but with a fixed or slightly variable demand size.

The condition ADI > x, CV2 > y shows the parts that have a rough demand structure, that is, the demand amounts can change excessively between periods and there are periods with many zero demands.

ADI ≤ x, CV2> y condition tests parts with high frequency of demand occurrence but irregular structure. In all these cases, x is the average inter-demand time with the limit value ADI = 1.32, which measures the average time between two consecutive requests, while y is the standard deviation of the period requirements divided by the average requirements, with the limit value CV2 = 0.49. is the coefficient of variation (Ghobbar & Friend, 2003).

ADI and CV2 parameters are calculated as follows.

$$ADI = \frac{\sum_{i=1}^{N} t_i}{N} \qquad (1)$$

$$CV^2 = \frac{\sqrt{\frac{\sum_{i=1}^{N}(\varepsilon_i - \varepsilon)^2}{N}}}{\varepsilon} \qquad (2)$$

εi= consumption of spare parts (pcs)

ti= time between two consecutive requests

In the CV2 formula, ε is equal to the average demand. In the ADI formula, N includes periods with nonzero demand, while in the CV2 formula, N includes all periods (Callegaro A., 2010).

Below is the figure illustrating the basic patterns in spare parts classification.

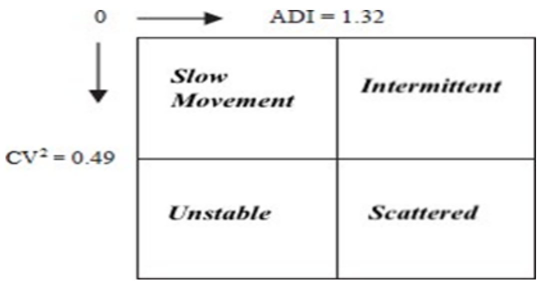

Figure 1.Demand Patterns (Callegaro A., 2010)

Syntetos and Boylan stated that, as a general comparison, the Syntetos-Boylan approach gives better results than the Croston and exponential smoothing methods when ADI > 1.32 and/or CV2 > 0.49 (Syntetos, 2005).

2.3. Information In the Literature On Demand Forecasting

Although demand forecasting methods such as moving averages and single exponential smoothing are still widely used in business, they overestimate discrete demand. Johnston and Boylan proposed the exponential weighted moving average method adjusted for discrete demand. This method gives better results if the time between requests is more than 1.25 compared to the classical method (Bacchetti & Saccani, 2012).

Altay et al. and Bermudez et al. have proposed a method for discrete demand forecasting with trend and seasonality by improving Holt and Holt-Winters methods. In stock level measurements, it was seen that these methods had higher confidence level and stock level, but did not make much difference in total costs. Croston has done a seminal work on intermittent demand forecasting. In the estimation process, he evaluated the demand size and the time between demands separately and applied single exponential smoothing in this philosophy. Syntetos and Boylan stated that Croston's estimator was biased and suggested a modified method with higher performance. Leven and Segerstedt proposed a method based on the Croston method, which is updated according to the ratio of the demand size and the inter-demand time only when there is positive demand. Bootstrap method is also used in the intermittent demand forecasting. This method does not require an assumption about the distribution of demand. Willemain modified the traditional bootstrap approach to account for autocorrelation in spare part demand, frequent recurring values, and relatively short series. In 9 industrial data sets, this method was compared with Croston and single exponential smoothing and achieved higher predictive accuracy. Kalchschmidt et al. focused on filtering demand data. He divided the demand into two structures as static and irregular. Single exponential smoothing is applied to the stationary time series, while the modified Croston procedure is applied to the irregular series.

As an alternative, Gutierrez et al. applied the neural network model to spare parts. In the dataset consisting of 24 time series, the neural network model produced better predictions than the single exponential smoothing, Croston and Syntetos-Boylan approach. Hua and Zhang applied the supporter vector machine in spare parts demand forecasting. With this method, it is aimed primarily to create non-zero demands and then to estimate the demand during the supply period. Ghodrati and Kumar used explanatory variables in demand forecasting. It has been stated that this method is difficult to implement because very specific information is required. Tibben-Lemke, Amato and Yamashina; They tried to forecast demand with the part failure function and the quantity of parts in use curves. Dolgui and Pashkevic developed a beta-binomial model for parts with a short demand history using the Bayesian paradigm. Traditional exponential smoothing and moving averages are still heavily used in business applications. Studies on the application of literature studies in real cases need to be increased (Bacchetti & Saccani, 2012).

2.4. Discrete Demand Forecasting Methods

A few of the demand forecasting methods selected for spare parts with discrete demand structure are mentioned under this title.

2.4.1. Single Exponential Smoothing

This method can be applied to time series when reasonable estimation for a short period is required. The value produced by smoothing historical demand data is extrapolated or extrapolated to form the future forecast. Exponential smoothing methods are applied to historical data with a set of weights that decrease exponentially over time. That is, the weight of the nearest demand value is higher. The general formula for this method is as follows. *Ft* is the smoothed predictive value, *Xt* is the actual value at time *t*, and *a* is the smoothing constant that takes values between 0-1.

$$F_{t+1} = \alpha X_t + (1-\alpha)F_t \qquad (3)$$

When there is a trend, the trend component should be considered alongside the mean of the series. In case the datasets are not stationary, it will be necessary to apply binary exponential smoothing and it is expressed as follows (Pham, 2006).

$$F''_{t+1} = \alpha F_{t+1} + (1-\alpha)F_t \qquad (4)$$

2.4.2 Croston Forecasting Method

The Croston method has been developed to more accurately calculate the average demand in each period. Like exponential smoothing, the Croston method assumes that the lead time follows a normal distribution. The work of Willemain et al. shows that Croston gives better results than exponential smoothing (Willemain, 2004).

The Croston method applies exponential smoothing to the time between nonzero demands and to demand magnitudes separately. I(t) is the average time between non-zero requests and S(t) represents the average demand size for non-zero requests. If q is defined as the last nonzero time interval, for X(t) = 0:

$$I(t) = I(t-1)$$
$$S(t) = S(t-1)$$
$$q = q+1$$

Otherwise;

$$S(t) = \alpha X(t) + (1-\alpha)S(t-1)$$
$$I(t) = \alpha q + (1-\alpha)I(t-1)$$
$$q = 1$$

By combining the demand size and range, the average demand in each period is as follows.

$$M(t) = S(t$$

These forecasts are updated only when demand occurs. Croston and exponential smoothing are identical when demand occurs at each review interval (Willemain, 2004).

2.4.3 Syntetos-Boylan Approach

A mathematical error made by Croston in calculating the expected size of demand was reported by Syntetos and Boylan. Syntetos and Boylan proposed a new approach to eliminate this bias. The revised model and the Croston method were tested by simulation study, and this corrected method presented improvements at a significance level of 0.01 Syntetos and Boylan stated that the expected value was calculated as μ/p in the Croston method, but the correct value was as follows.

$$E(F_t) = \frac{\mu}{p}\left(1 + \frac{\alpha}{2-\alpha} . \frac{p-1}{p}\right) \qquad (6)$$

In this formula, α is the smoothing constant, Ftis the forecast value, μ is the average of the demand data, and p is the average of the inter-demand time. However, the new estimator is expressed by the following equation (Syntetos & Boylan, 2001).

$$F_{t+1} = \left(1 - \frac{\alpha}{2}\right) . \frac{X_t}{P_t} \qquad (7)$$

When the time between non-zero requests is small, that is, when 1/p is large, the error in the Croston method is low, while with the Syntetos-Boylan approach, it is less inaccurate in cases where there are many zero requests, that is, 1/p is small.

2.4.4 Bootstrap Forecasting Method

Willemain et al. adapted the Bootstrap method to data with discrete demand. Modifying Efron's 1979 work, a method has been developed that responds to three difficult characteristics of discrete demand: autocorrelation, frequent values, and relatively short series. Autocorrelation is expressed by a bistable and first-order Markov process. In this way, the prediction sequence of zero and non-zero values in the procurement process was obtained. Then, a random nonzero value is selected and random variation is added to it. In this way, variation is increased for large demands. Let X* be a randomly selected value from historical demand data and Z represent the standard normal deviation. Incidental variance addition (diversion) is done by the following logic (Willemain, 2004).

$$DIVERSION = 1 + INTEGER\{X^* + Z\sqrt{X^*}\} \quad (8)$$

$$IFDIVERSIONIS \leq 0DIVERSION = X^* \quad (9)$$

Adding random variation increases the accuracy of the forecast, especially for short lead times. Collecting the demands in the lead time for each period creates 1 forecast. The steps of the Bootstrap approach are given below (Willemain, 2004).

Step 1: Historical demand data for a certain time period is collected.

Step 2: The transition probabilities for the two-state Markov model (zero and non- zero demand values) are calculated.

Step 3: According to the last observed demand, a zero/non-zero range of values is generated using the Markov model.

Step 4: All state markers with nonzero numeric values are randomly sampled instead of nonzero requests in the observed claim set.

Step 5: Nonzero requests are deflected.

Step 6: Forecast values are collected for periods within the lead time.

Step 7: Steps 2-5 are repeated many times.

Step 8: The resulting lead time demand values are sorted and used.

3. STOCK CONTROL OF REPAIRABLE SPARE PARTS

When demand is estimated with parametric approaches, information about the average and variance of demand is obtained. In addition, as in most stock control applications, it is necessary to hypothesize about demand distributions. This is necessary to determine the amounts of interest. Information on demand distributions is given in the next section (Altay, 2011).

3.1 Demand Distributions

Parts in a discrete demand structure are identified by their infrequent, variable-size and irregular-range demands. Elements such as demand size and time between requests are often used to model these parts. It is therefore normal for composite theoretical distributions to be applied in these parts. If time is defined as a discrete variable, the demand can be generated according to the Bernoulli process, which ensures that the inter-demand time is geometrically distributed. When time is seen as a continuous variable, the time between requests is in a negative exponential distribution (Altay, 2011).

There are theories that support the use of both geometric and exponential distributions to represent time between consecutive demands. Dunsmuir and Snyder, Kwan, Willemain et al., Janssen and Eaves have worked on this. With the arrival of the demands being Poisson and the demand sizes being random, the distribution for a fixed lead time is the composite binomial distribution. Gallagher, Ward and Watson studied the formation of demand Poisson and composite Poisson distributions, whose demand size is a geometric distribution. Poisson-normal distribution combinations have also been studied, but for lumpy demands the distribution tilts to the right, breaking the normality assumptions. Quenouille showed that the Poisson-Logarithmic process produces the negative binomial distribution. Another distribution representing the demand is the Gamma distribution. The Gamma distribution is the continuous analog of the Negative Binomial Distribution. The gamma distribution contains many different distribution formats and has a place in stock control applications for non-zero values. While the normal distribution is not very suitable for expressing demand magnitudes, it is a reasonable assumption for lead times, especially when they are long. The assumption of normality is also likely when the squared coefficient of variation (CV2) of demand in each period is low. Syntetos et al.; Poisson, Negative Binomial, Geometric Poisson, Gamma and Normal distributions were tested for the degree of fit (Altay, 2011).

3.2 Repairable Spare Parts Stock Control Models

In this section, multi-stage spare and repairable spare parts inventory management models will be briefly mentioned. Defective parts create demand and stock from the central warehouse is used to meet this demand. The defective part enters the repair cycle. These models are; There are Metric models, Multistage heap models, Distribution-oriented models, Simulation-based heap models, One-to-One heap models, and queuing-based heap models and application-based models.

4. DEMAND FORECAST AND STOCK CONTROL APPLICATION FOR AIRCRAFT SPARE PARTS

In the application, the weekly demands of the 10 critical aircraft components used in the inventory of a maintenance-repair organization in the aviation sector in the last 5 years have been taken. The demand structure of the parts was examined. Classification methods and their accuracy with mean error were tested and estimation data were produced for the best method. In the last stage, it is calculated how much stock the firm should keep under various distributions at the confidence level determined. CRAN R 3.3.1 software package was used in the application process.

4.1 Demand Classification Of Time Series Data

Before estimating spare parts, classification is necessary to understand the nature of demand. Because different estimation techniques give better results in different classifications. The demand structure of the parts was determined by using the tsintermittent package in the R software. The table below gives information about which estimation method the parts are more suitable for, according to the classification of Syntetos-Boylan. The limit values used in the classification are 0.49 for CV2and 1.32 for p, as seen in the chart below.

Table 1

Syntetos-Boylan Classification Values of Parts

	Part1	Part2	Part3	Part4	Part5	Part6	Part7	Part8	Part9	Part10
Croston								X	X	X
SBA	X	X	X	X	X	X	X			
CV^2	0,469	0,285	0,442	0,352	0,318	0,167	0,228	0,392	0,423	0,432
P	1,581	3,638	1,627	1,578	2,534	4,654	3,583	1,015	1,065	1,290

When we examine the graph above, three spare parts that make up our data set are suitable for the Croston demand forecasting method according to the classification of Syntetos-Boylan, while the other seven spare parts seem to be suitable for the Syntetos- Boylan approach. While Croston gives good results in smooth demands, Syntetos-Boylan approach is used in demand patterns that we call lumpy. Since the demand for aircraft spare parts can change a lot over time or periodically, it is not surprising that the number of spare parts that fit the properly qualified classification is low.

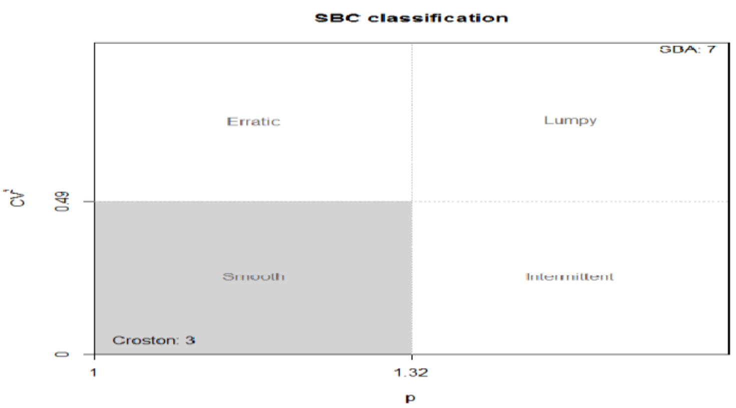

Figure 2. Syntetos Boylan Classification Graph

Our next step will be to compare their errors using some estimation methods.

4.2 Use and Comparison of Some Demand Forecasting Methods

Aircraft spare parts can fit very different demand patterns and often the demands are not evenly distributed and have high variance. The reason for this is that the number of aircraft in the fleet changes over time and there are periodic fluctuations in the demands of some components. In this section, three demand forecasting methods were applied to the data set in the appendix of the study, taking into account the structure of the demand for aircraft spare parts. As can be seen in the dataset, the demand for parts was zero in some weeks. This is related to the intermittent demand structure observed in most aircraft parts. In such cases, applying special estimation techniques gives better results. For this reason, in this study, Croston, Syntetos-Boylan approach and Single Exponential Correction methods included in the CRAN R tsintermittent package were used. When we examine the R outputs, for example, as a result of applying the Croston method for Part 4, the weights for demand and interval are 0.2022765 and 0.0694567, respectively. Since Croston produces linear estimates, the value we obtained is calculated as 2.765479.

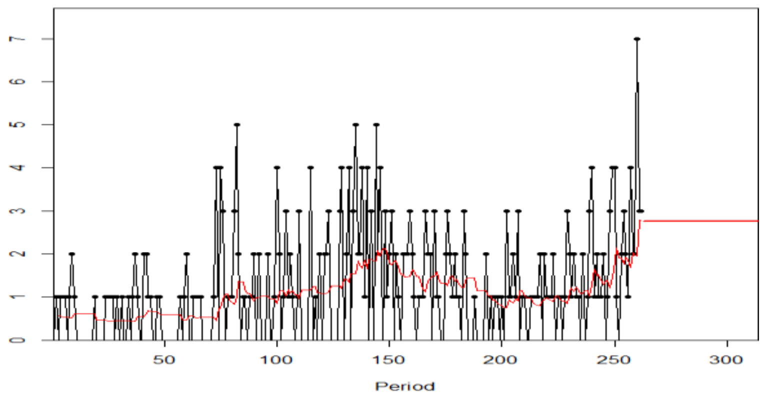

Figure 3.Demand Time Series And Croston Forecast Graph For Part4

The chart above shows the actual demand values for Part 4 (in black) and the values generated by the Croston forecast calculation (red). When we analyze Part 7 with the Syntetos Boylan approach, we can see that the demand is a little more stable and there are occasional fluctuations. The demand and range weights for this method were found to be 0.46615481 and 0.06193175, respectively. The estimated value produced is 0.2705005. Details on the implementation of all methods are additionally shared in the relevant Excel file. Demand forecast of all parts was made using the three methods mentioned above and finally the best method was determined by calculating the average errors.

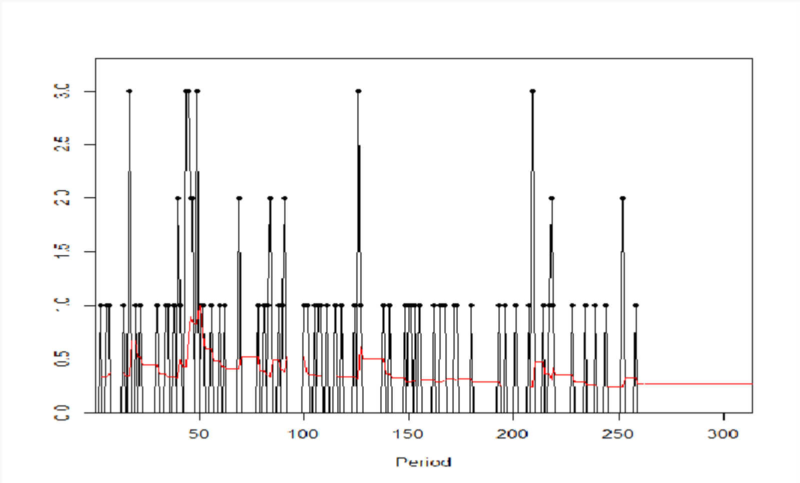

Figure 4.Demand Time Series And Syntetos Boylan Forecast Graph For Part7

Below is a table of mean errors. Values highlighted in green indicate the lowest errors. Accordingly, the Croston estimation method gave the most accurate estimation results for 8 out of 10 items, while the Syntetos Boylan approach gave the least erroneous results for the remaining 2 items. It can be seen from the obtained results that the use of the Single Exponential Correction method in estimating the demand for aircraft spare parts is not very accurate. Forecasting methods, which are Croston and its derivatives, give good results because they weight both demand and demand intervals, that is, considering how many periods the demand occurs.

Table 2

Mean Error (MSE) Values For The Three Estimation Methods

	Part1	Part2	Part3	Part4	Part5	Part6	Part7	Part8	Part9	Part10
Croston	1,7696	0,53031	1,61868	1,42561	0,71263	0,27760	0,4206	19,9114	5,55550	3,00614
SBA	1,7696	0,53535	1,62109	1,43502	0,71370	0,27685	0,41964	19,9343	5,59891	3,07774
SES	1,7754	0,53371	1,62299	1,43154	0,72586	0,28394	0,42552	19,9848	5,55967	3,04303

4.3 Stock Control for Aircraft Spare Parts

Stock control of spare parts has a critical importance in the aviation maintenance- repair industry. Since idle inventory will cause financial loss, companies must keep sufficient stocks on hand. In this sector, the Poisson distribution is mostly preferred for stock control. It provides convenience as a single parameter λ, that is, the demand occurring in a certain period or the frequency of failure, is used in the calculation. In this section, Poisson distribution as well as Negative Binomial and Polya-Aeppli distributions are shown in practice as a stock control method for repairable aircraft parts with mostly intermittent demand structure. Poisson has the disadvantage because it does not take variability into account in inventory control. In cases where variability is high, it would be healthy to use Negative Binomial or Polya-Aeppli distributions.

4.3.1 Repairable Aircraft Parts and Their Conversion

Before doing stock control analysis for aircraft spare parts, it would be correct to know which cycle the typical spare parts go through in Maintenance and Repair organizations. The key elements of the repair cycle must be well analyzed for the management of the component inventory, which are repairable aircraft parts. These items are:

While component is in the air (MTBF, MTBR, MTBUR): It is the time between the installation of the component on the aircraft and its removal due to a malfunction. Statistical parameters at this stage such as MTBF (Mean Time Between Failures), MTBR (Mean Time Between Breaks), MTBUR (Mean Time Between Unplanned Removals) are used to reveal the component's demand pattern.

While the component is waiting for repair (core unit): It covers the period from when the component is removed from the aircraft due to malfunction until it is shipped to the repair service provider. In this process, in terms of tracking the moving inventory, by placing the RFID tags on the component, where and in which condition the parts are will be better known and this will eliminate the uncertainties.

During Repair (TAT): It includes the time that the repair station or workshop physically receives, inspects, and repairs the part. Repair time should be well studied for effective inventory management because the effect of this time on determining the stock level is undeniable.

It refers to the time that the component spends in the warehouse waiting for its demand. The number of spare parts waiting to be used should be well studied. If the average stock has a large amount of spares waiting for demand, it indicates that the inventory is not well managed. FIFO, the first in, first out rule, is an inventory strategy that allows efficient use of the shelf life of spare parts (Alfieri, 2014). The following figure shows the component circulation in plain form.

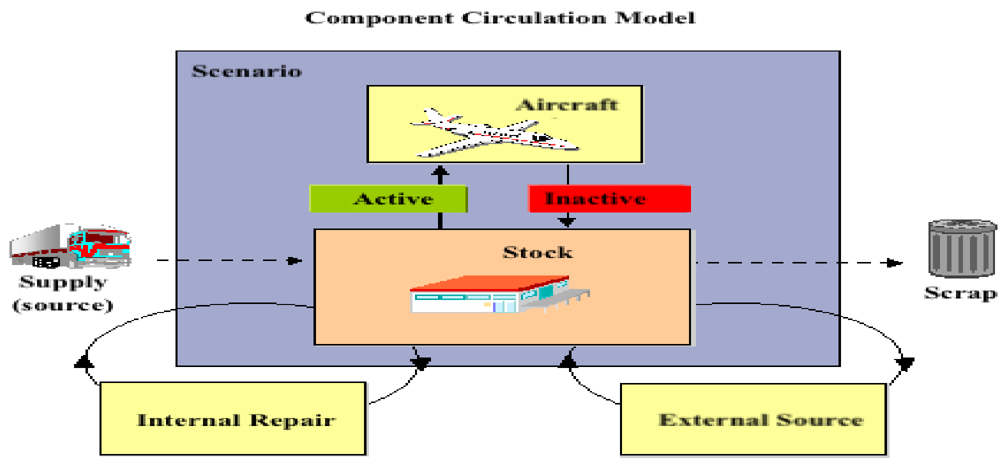

Figure 5.Component Circulation Model (Maintenance Planning-Spare Parts Stock Calculation)

4.3.2 Matching Demand to Distributions In Stock Control

As seen in the component circulation, the important point when calculating stock control is to determine the number of requests or malfunctions from the spare part's dismantling due to a malfunction to its active entry into the warehouse, and to calculate the required spare amount according to the desired confidence level. The formula for calculating this value is given below. Since we have direct weekly demand values, we used the formula when calculating the expected demand.

$$E = \frac{FHxQPAxN}{MTBUR} \cdot \frac{TAT}{365} = \frac{D}{7} \qquad (10)$$

E = expected demand

D = weekly demand

FH = annual flight hour

QPA = quantity per aircraft

N = number of aircraft in the fleet

MTBUR = mean time (hours) between unscheduled removals

TAT = turnaround time (days)

The inference we will make from this formula is that TAT is directly proportional to E value and MTBUR is inversely proportional to E. We can define E as the possible demand that may be encountered when the component is not available in the warehouse due to a malfunction. For example, if the number of weekly failures from a component is D = 2 units/week and TAT = 42 days, the expected demand will be E = 2 x 42/7 = 12.

Therefore, if we want to minimize the inventory level in repairable spare parts stock control, some actions must be taken to reduce the TAT cycle time or increase the MTBUR average part failure time. The expected demand calculations mentioned in the table below are made and the results are shown.

Table 3

Table of Expected Demand Calculated For Each Part

Part	Average Demand per Week	TAT (days)	Expected Demand
Part1	1,210	44	7,605
Part2	0,382	51	2,781
Part3	1,137	31	5,037
Part4	1,195	24	4,096
Part5	0,584	36	3,003
Part6	0,256	22	0,804
Part7	0,351	84	4,214
Part8	7,847	8	8,968
Part9	3,992	10	5,703
Part10	2,061	8	2,356

Here, the expected demand, which we calculated with the value of E, represents λ in the Poisson distribution. In other words, when we obtain this value, we can calculate the desired reserve amount by taking the inverse of the Poisson distribution together with the confidence level. However, in Negative Binomial and Polya-Aeppli distributions, unlike Poisson, the size (number of successful trials) and the probability of success in each trial or the geometric distribution parameters also come into play or because the number of parameters increases, transformation is required. These distributions also take into account the variance in demand.

For the Negative Binomial distribution, the r and p values must be calculated. By calculating the expected demand and variance from the demand series, we can find the r and p values with the following formulas (Fukuda).

$$p = \frac{\mu}{\sigma^2} = \frac{\text{expecteddemand (a}}{\text{variance}} \tag{11}$$

$$r = \frac{p.\mu}{(1-p)} = \frac{\text{(expecteddeman}}{\text{variance} - \text{expectedd}} \tag{12}$$

For the Polya-Aeppli (Geometric Poisson) distribution, λ and p calculations are required. These parameters can be found with the following equations (Burden, 2014).

$$\lambda = \frac{2\mu^2}{\sigma^2 + \mu} = \frac{2.\text{(expecteddema}}{\text{variance} + \text{expectedd}} \tag{13}$$

$$p = \frac{\sigma^2 - \mu}{\sigma^2 + \mu} = \frac{\text{variance} - \text{expectedd}}{\text{variance} + \text{expectedd}} \tag{14}$$

The average and variance values to be used in the inventory control calculation are given in the table below for our 10 spare parts. The variances of the estimated demand values calculated are significantly lower than the variances of the actual demand values, and their use in stock control will not be appropriate as it will cause misdirection in stock control. Therefore, we made our backup calculations based on real demand data.

Table 4

Average Demand, Forecast And Variance Values of Aircraft Spare Parts

	Avg. Demand Forecast	Avg. Actual Demand	Forecast Variance	Actual Demand Variance	Variance / Average (Forecast)	Variance / Average (Actual)
Part1	7,87692168	7,60523446	7,29511666	77,1212235	0,92613802	10,140545
Part2	2,66283790	2,780806979	0,44508443	28,4387513	0,16714665	10,226798
Part3	4,70290606	5,037077426	4,04896983	34,1939441	0,86095061	6,7884491
Part4	3,71807395	4,095965104	2,51472696	19,0546384	0,67635206	4,6520509
Part5	3,06408207	3,003271538	2,26902666	21,2455909	0,74052411	7,0741492
Part6	0,90531456	0,803707743	0,19369653	2,94685616	0,21395496	3,6665768
Part7	4,59607680	4,213740458	2,37739445	61,6246380	0,51726604	14,624687
Part8	8,61802442	8,968375136	10,3405712	33,3381155	1,19987723	3,7172971
Part9	5,39616025	5,703380589	5,89644811	16,7799259	1,09271183	2,9421017
Part10	2,57951169	2,355507088	0,69046258	4,70916143	0,26767182	1,9992134

When we examine the variance/mean ratios, we see that all of them are greater than 1 for real demand values. This means that the use of the Poisson distribution in stock control will cause the reserves to be underestimated and will not be able to keep up with the variation available. The Poisson distribution, by its nature, will give the most accurate result if the variance is equal to or close to the mean. Negative Binomial and Polya Aeppli distributions will give more reliable results when demand variability is high. However, utilizing the Poisson distribution for non-critical parts can bring cost advantages, although it increases the risk of problems in stock management. By substituting the mean and variance values calculated in the above transformation formulas, we can determine the reserve levels for the distributions that are the subject of our study. The following backup calculations were made for 96% confidence level by writing the relevant parameters in qpois(), qnbinom(), qPolya-Aeppli() functions in CRAN R software.

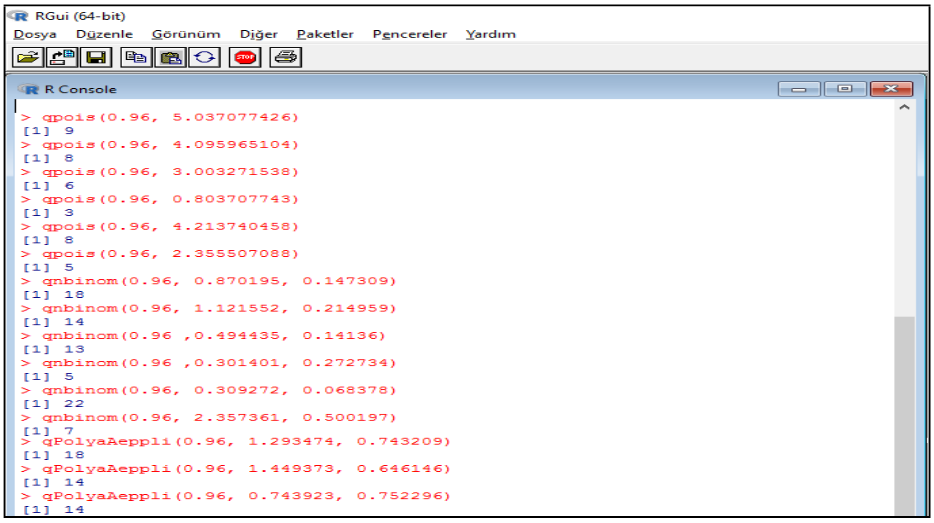

Figure 6. R Software Interface (Scatter Calculations)

Table 5

Poisson, Negative Binomial, And Polya-Aeppli Parameters and Suggested Replacement Numbers

	Poisson λ	NB r	NB p	P-A λ	P-A p	Poisson Spare	NB Spare	P-A Spare
Part1	7,60523446	0,8320	0,0986	1,3653	0,8204	13	27	27
Part2	2,78080697	0,3013	0,0977	0,4953	0,8218	6	15	15
Part3	5,0370774	0,8701	0,1473	1,2934	0,7432	9	18	18
Part4	4,09596510	1,1215	0,2149	1,4493	0,6461	8	14	14
Part5	3,00327153	0,4944	0,1413	0,7439	0,7522	6	13	14
Part6	0,80370774	0,3014	0,2727	0,3444	0,5714	3	5	5
Part7	4,21374045	0,3092	0,0683	0,5393	0,8719	8	22	23
Part8	8,96837513	3,3004	0,2690	3,8023	0,5760	15	21	21
Part9	5,70338058	2,9367	0,3398	2,8935	0,4926	10	14	14
Part10	2,3555070	2,3573	0,5001	1,5707	0,3331	5	7	7

In the spare calculations, it has been observed that the recommended spares for the Negative Binomial and Polya-Aeppli distributions in the parts with high variance are relatively high compared to the Poisson distribution. This is because the variance/expected demand ratios are high for the majority of parts. In addition, demands were measured on a weekly basis. If we renew our calculations by clustering the demands on a 4-week basis, both the variance and the suggested spare numbers will be lower. This will reduce the inventory items and costs that must be kept in inventory management. When we add the demands to cover 4 weeks and make our calculations again for 65 periods, the following results emerge. Here, we see that the variances decrease with the effect of clustering. Negative Binomial and Polya-Aeppli distribution will not be used because the Variance/Mean ratio for Part 10 falls below 1.

Table 6

Distribution Parameters And Some Statistics For The New Scenario

	Avg. Demand	Demand Variance	Poisson Λ	NB r	NB p	P-A λ	P-A p	Variance / Average
Part1	7,63956	30,1633	7,6395	2,59117	0,2532	3,08775	0,5958	3,948307527
Part2	2,77418	7,47577	2,7741	1,63690	0,3710	1,50168	0,4586	2,694771374
Part3	5,02473	13,5246	5,0247	2,97036	0,3715	2,72223	0,4582	2,691623789
Part4	4,04835	7,31268	4,0483	5,02069	0,5536	2,88515	0,2873	1,806334342
Part5	3,00659	8,22795	3,0065	1,73127	0,3654	1,60925	0,4647	2,736636513
Part6	0,80989	0,98330	0,8098	3,78243	0,8236	0,73157	0,0967	1,214119136
Part7	4,24615	18,2509	4,2461	1,28740	0,2326	1,60286	0,6225	4,298233696
Part8	9,01099	17,1022	9,0109	10,0352	0,5268	6,21891	0,3098	1,897931185
Part9	5,65385	9,38125	5,6538	8,57592	0,6026	4,25218	0,2479	1,659269575
Part10	2,34286	2,17908	2,3428	-	-	-	-	0,930095819

The comparison of the reserve numbers calculated with the weekly demand data and the reserve numbers calculated by combining the 4-week demands are given in the table below according to the distributions. Combining the demands for 4 weeks caused the variance to decrease and the suggested reserve amounts decreased except for the Poisson distribution.

Table 7

Calculation Of Reserves By Distribution In Two Different Scenarios

Weekly Demand			4 Week Demand		
Poisson Spare	**NB Spare**	**P-A Spare**	**Poisson Spare**	**NB Spare**	**P-A Spare**
13	27	27	13	19	19
6	15	15	6	9	9
9	18	18	9	13	13
8	14	14	8	10	10
6	13	14	6	9	9
3	5	5	3	3	3
8	22	23	8	14	13
15	21	21	15	17	17
10	14	14	10	12	12
5	7	7	5	-	-

All these results show that it would be appropriate to use Negative Binomial or Polya-Aeppli distributions for spare parts with high demand fluctuations. Poisson, on the other hand, will be a reliable stock control tool for parts with a more stable demand structure.

5. CONCLUSION AND EVALUATION

In the study, some demand forecasting and stock control methods were applied for 10 different repairable spare parts (components) that we bought from a well-established aircraft maintenance-repair company. In order to make a correct demand forecast, first of all, the demand patterns of the parts were determined by the classification methods available in the literature, and then valuable information for future planning was obtained by applying forecasting techniques that are suitable for historical demand data. The demand structure of aircraft components can be very different. Generally, the demands are irregular and there may be situations where the demand is zero at certain periods. Therefore, some special forecasting methods are used for demand forecasting in these parts.

In the study, the accuracy of which was examined; Croston, Syntetos Boylan Approximation and Single Exponential Smoothing techniques were compared by taking mean squared errors (MSE). Croston gave the lowest erroneous results for most part estimates. It has been seen that the Croston method can be easily used in estimating the demand for non-uniform and intermittent spare parts. The next step after the estimation was the development of a reliable stock control mechanism for aircraft spare parts. Neither too much nor too little must be kept in sufficient reserve storage for the operation to run smoothly. The most popular inventory control tool in aviation is the Poisson distribution. However, because Poisson does not take into account the dramatic fluctuations in demand, it will often not be a safe tool for modeling demand. Almost all of the variance/mean values obtained from the data set were greater than 1. Because of this excessive dispersion, it would be more appropriate to use Negative Binomial or Polya-Aeppli distributions in aircraft components. Quite simply, it would be the right decision to decide according to the variance/mean ratios for the distribution to be used. We applied all three distributions mentioned above on the data set. When the calculated reserve numbers are examined, Poisson always gave the lowest reserve numbers. The other two distributions suggested higher reserve amounts because they took into account the variability. In order to make up for this difference a little, the reserve amounts were calculated by combining the demands for four weeks. In this case, better and satisfactory results have been achieved. In the future, this forecasting and inventory control analysis can be further developed and expanded. For example, the demand for spare parts; It may depend on parameters such as the number of aircraft in the fleet and some planned changes. By performing multiple regression analysis involving these parameters, the demand structure of the components can be analyzed more deeply. I consider that this study can contribute to other studies in this field.

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ATTACHMENT A

Table

262 weeks (5 years) demand values for 10 different aircraft components

Week	Part1	Part2	Part3	Part4	Part5	Part6	Part7	Part8	Part9	Part10
1	0	0	0	0	0	0	0	2	1	0
2	0	0	0	1	0	1	0	4	7	1
3	0	1	2	0	1	0	1	2	3	0
4	0	0	0	1	0	0	0	1	0	1
5	0	0	1	1	1	0	0	4	3	0
6	0	0	0	1	0	0	1	2	1	0
7	0	0	0	0	0	1	1	2	2	4
8	0	0	2	1	0	0	0	2	3	2
9	1	0	0	2	3	2	0	4	1	0
10	0	0	1	1	0	0	0	8	0	0
11	0	0	2	0	2	0	0	5	1	1
12	0	0	2	0	0	0	0	5	2	0
13	1	0	0	0	1	1	0	7	3	0
14	0	0	0	0	0	0	1	3	0	0
15	0	1	1	0	0	0	0	11	0	0
16	0	0	0	0	0	0	0	1	2	0
17	0	0	1	0	0	1	3	4	2	0

18	0	1	1	0	0	0	0	6	0	1
19	1	0	0	1	0	3	0	7	0	0
20	1	2	0	0	0	2	1	7	3	3
21	2	0	0	0	0	0	0	7	2	1
22	0	0	1	0	0	0	1	5	6	1
23	2	0	0	0	1	0	0	8	2	1
24	1	0	1	1	0	2	0	3	2	0
25	0	0	1	1	0	1	0	2	3	0
26	2	0	1	1	0	0	0	1	1	0
27	3	0	0	1	0	1	0	5	1	1
28	1	0	1	0	0	1	0	3	2	1
29	1	1	0	1	0	0	0	4	5	1
30	0	1	0	0	1	2	1	6	1	4
31	2	0	1	1	0	0	0	5	1	4
32	1	1	0	0	0	0	0	8	5	1
33	0	0	0	0	0	0	0	5	2	2
34	0	0	0	1	1	1	1	7	7	0
35	1	1	0	0	0	0	1	4	2	2
36	2	0	1	1	1	1	0	3	3	2
37	0	1	0	2	0	0	0	13	3	1

38	2	2	0	1	3	0	1	4	1	2
39	0	0	0	0	0	0	0	0	1	3
40	0	1	2	0	0	0	2	10	0	2
41	1	0	1	2	0	0	1	8	1	4
42	0	1	0	2	0	0	0	6	3	4
43	1	0	2	1	0	0	0	14	0	0
44	1	0	0	1	0	0	3	9	4	2
45	0	0	0	0	0	1	3	11	2	1
46	2	0	0	0	0	0	2	4	2	2
47	1	0	1	1	0	2	2	5	2	4
48	3	0	0	1	0	1	0	3	1	2
49	0	0	0	0	0	0	3	6	2	0
50	0	0	0	0	0	0	0	2	0	2
51	0	0	0	0	0	0	1	8	0	1
52	0	0	0	0	0	0	1	7	3	2
53	1	1	2	0	1	0	0	3	1	4
54	1	0	0	0	0	0	0	7	3	0
55	1	0	2	0	0	0	0	6	3	4
56	0	0	0	0	0	0	1	4	4	0
57	0	1	0	1	0	0	0	4	3	4

58	0	0	0	0	0	1	0	5	6	0
59	0	0	1	1	0	0	0	6	1	3
60	0	0	0	2	0	0	1	8	3	3
61	2	0	0	0	1	0	0	7	3	0
62	0	1	0	0	0	1	1	5	4	3
63	0	0	2	1	0	2	0	5	3	1
64	1	0	1	1	0	1	0	4	0	0
65	1	0	1	1	0	0	0	9	2	1
66	3	0	0	1	1	3	0	12	2	3
67	1	0	1	0	0	1	0	2	4	0
68	1	0	0	0	0	0	0	8	3	2
69	1	0	0	0	0	1	2	6	6	0
70	1	1	1	0	0	0	0	6	2	3
71	0	0	0	0	0	2	0	7	1	2
72	1	1	0	1	0	0	0	1	5	3
73	1	0	0	4	0	1	0	1	4	0
74	1	0	0	0	0	0	0	2	4	1
75	0	1	4	4	0	0	0	1	3	0
76	2	0	1	3	0	1	0	0	0	1
77	2	0	1	0	0	0	0	3	3	1

78	0	0	0	1	0	0	1	4	2	2
79	0	0	4	1	0	1	0	10	2	0
80	1	1	0	1	1	1	0	9	2	0
81	0	0	3	3	0	0	1	8	3	2
82	2	0	0	5	0	0	0	5	4	1
83	2	1	1	2	0	0	1	4	2	0
84	4	0	0	0	0	0	2	1	2	0
85	1	0	0	1	1	0	0	9	3	3
86	1	0	1	1	0	0	0	8	2	4
87	0	2	0	0	0	1	0	18	5	1
88	0	0	1	1	0	0	1	8	6	1
89	0	1	2	1	1	0	0	5	3	0
90	0	0	1	2	0	0	1	7	4	1
91	0	4	1	0	0	0	2	8	6	1
92	0	0	0	2	0	0	0	7	3	0
93	1	0	1	0	1	0	0	5	0	1
94	0	2	0	0	0	2	0	8	2	2
95	2	0	0	0	1	1	0	3	4	3
96	3	0	0	2	1	0	0	6	2	1
97	0	0	1	0	0	0	0	7	4	0

98	1	0	1	0	0	1	0	1	2	1
99	2	0	0	1	0	1	0	3	1	1
100	0	0	1	4	0	1	1	6	4	2
101	1	1	1	2	0	0	1	4	2	2
102	0	0	0	0	2	0	1	3	5	0
103	2	1	2	1	0	0	0	10	3	0
104	6	1	2	3	0	0	0	4	1	1
105	0	0	0	1	0	0	1	4	1	3
106	1	1	1	2	0	0	0	4	4	5
107	0	0	1	1	0	0	1	3	8	2
108	4	0	2	0	1	1	1	2	2	4
109	2	0	1	1	0	0	0	13	2	2
110	2	1	1	3	0	0	0	9	7	2
111	1	0	2	0	0	0	1	6	4	1
112	0	0	5	0	0	0	0	8	1	0
113	0	0	0	0	1	0	0	10	1	3
114	1	0	3	0	0	0	0	6	0	4
115	0	0	2	4	1	0	1	13	1	2
116	0	0	0	0	0	0	0	11	3	3
117	0	0	1	1	0	0	0	8	3	1

118	0	0	0	0	1	0	1	10	1	3
119	1	0	0	2	1	0	0	8	2	0
120	0	1	0	0	2	0	0	12	9	0
121	0	0	4	2	1	0	0	10	5	0
122	1	0	0	2	1	1	0	13	3	1
123	1	0	0	3	0	0	0	5	0	4
124	0	0	2	0	2	0	1	11	8	1
125	1	0	3	0	0	0	0	3	1	0
126	1	0	4	0	1	1	3	4	4	3
127	0	0	1	0	1	0	1	14	6	2
128	2	0	0	3	0	0	0	5	2	0
129	0	3	1	4	0	0	0	3	6	6
130	0	2	5	0	0	0	0	3	7	2
131	2	0	9	2	0	1	0	10	6	3
132	1	0	7	4	1	0	0	6	1	2
133	0	0	3	0	0	0	0	7	8	1
134	1	0	4	3	0	0	0	10	5	0
135	0	1	0	5	0	0	0	9	5	3
136	1	0	2	2	1	1	0	6	6	3
137	1	0	4	2	0	0	0	5	4	1

138	2	0	3	4	1	0	1	9	10	2
139	5	0	0	1	0	0	0	5	2	1
140	0	0	0	4	1	0	0	9	0	3
141	3	2	1	0	0	0	1	7	4	5
142	0	0	1	3	1	0	0	16	5	3
143	1	0	0	0	0	1	0	11	6	2
144	0	0	1	5	1	0	0	5	4	2
145	0	0	2	2	0	0	0	13	3	5
146	0	0	0	4	1	0	0	17	5	3
147	2	0	1	0	0	0	0	13	6	2
148	3	1	2	3	0	0	1	8	3	2
149	2	0	2	1	0	0	0	7	2	4
150	1	1	2	2	1	0	1	5	3	1
151	0	0	1	3	0	0	1	6	4	0
152	2	0	2	0	2	0	0	0	3	4
153	3	0	3	2	2	0	1	11	4	3
154	1	1	2	1	2	1	0	4	4	0
155	1	0	2	0	0	1	1	3	8	2
156	1	0	2	2	2	0	0	5	3	4
157	1	0	0	2	3	0	0	5	4	1

158	0	1	1	2	1	0	0	7	3	2
159	2	0	0	3	0	1	0	10	1	6
160	0	0	1	2	0	0	0	10	5	0
161	1	0	0	1	0	0	0	14	1	2
162	1	0	3	0	1	0	1	9	1	4
163	5	1	0	1	0	0	0	8	2	4
164	0	2	3	1	0	0	0	2	2	1
165	1	0	1	1	0	0	1	9	5	1
166	1	1	2	3	1	0	1	5	9	4
167	2	2	1	2	0	0	1	3	3	4
168	3	0	1	2	0	0	0	13	3	0
169	0	1	0	0	0	1	0	8	2	2
170	0	0	0	3	0	0	0	3	3	0
171	1	0	1	1	1	0	0	12	6	1
172	1	0	1	1	0	0	1	11	5	2
173	1	0	1	0	1	0	1	12	8	0
174	1	0	1	0	1	0	0	15	4	0
175	0	0	0	2	0	0	0	6	5	1
176	1	1	3	3	0	0	0	1	4	0
177	1	0	0	2	0	0	0	4	1	2

178	1	0	1	1	4	0	0	11	3	1
179	1	0	2	2	0	0	0	4	1	2
180	2	0	3	1	2	0	1	10	3	1
181	2	0	1	1	3	0	0	6	4	2
182	4	1	0	0	3	0	0	14	4	3
183	2	0	1	3	1	0	0	12	4	3
184	1	1	0	2	2	1	0	6	2	3
185	0	2	0	0	1	0	0	12	10	3
186	1	0	3	0	0	0	0	7	6	3
187	1	0	2	0	1	0	0	7	9	2
188	3	1	1	1	0	0	0	12	6	3
189	3	0	0	0	1	1	0	6	4	5
190	3	0	3	0	0	0	0	15	3	4
191	2	0	2	0	3	0	0	8	1	1
192	3	0	0	0	0	0	0	12	8	3
193	6	0	1	2	0	0	1	10	5	4
194	6	0	1	0	0	0	0	10	7	6
195	1	1	1	1	0	0	0	9	7	1
196	4	2	0	0	0	0	1	5	6	3
197	2	1	3	1	2	0	0	9	1	0

198	1	0	1	1	0	0	0	6	2	1
199	2	0	2	0	1	0	0	8	1	2
200	0	0	3	1	0	0	0	8	4	3
201	0	0	0	0	2	0	1	4	6	6
202	2	0	2	3	1	1	0	10	5	5
203	4	2	2	1	1	0	0	17	5	2
204	4	0	1	1	1	0	0	12	4	1
205	2	0	1	2	1	1	0	10	4	0
206	2	2	1	1	0	0	0	6	3	4
207	3	1	3	3	2	0	1	12	2	2
208	1	0	4	0	0	0	0	7	4	0
209	8	1	4	1	1	0	3	5	4	1
210	3	0	3	1	2	0	0	10	7	2
211	1	1	0	0	1	0	0	7	4	4
212	0	0	1	0	1	0	0	10	5	1
213	1	0	1	1	1	0	0	9	9	4
214	1	0	1	1	0	0	1	7	4	0
215	4	1	2	1	1	0	0	3	7	0
216	1	0	0	1	1	0	0	6	4	1
217	2	0	0	2	1	0	1	7	2	0

218	1	0	2	0	0	0	2	20	6	1
219	1	2	1	2	0	0	1	16	5	1
220	1	0	3	1	0	0	0	7	2	1
221	0	0	1	1	0	0	0	10	5	3
222	3	0	2	1	1	0	0	5	4	1
223	0	0	1	2	0	1	0	5	5	0
224	1	0	0	0	1	0	0	5	6	2
225	1	0	1	1	0	0	0	6	10	3
226	1	1	0	1	1	0	0	12	9	4
227	1	0	1	0	5	0	0	12	3	1
228	2	1	1	1	2	1	1	16	9	3
229	3	0	1	3	0	0	0	9	3	2
230	3	0	0	2	3	0	0	5	8	5
231	1	0	1	1	2	0	0	10	9	4
232	3	0	3	2	0	0	0	11	6	7
233	1	0	2	1	0	0	0	13	2	4
234	5	0	0	1	1	0	1	13	6	4
235	7	0	0	0	2	1	0	3	4	9
236	3	4	1	2	1	0	0	17	9	2
237	2	1	2	0	1	0	0	14	9	3

238	1	0	2	1	0	0	0	2	10	4
239	1	0	3	3	0	0	1	11	6	2
240	3	0	2	4	0	0	0	8	10	3
241	0	0	0	1	1	0	0	6	12	2
242	1	1	1	2	1	0	0	27	10	5
243	0	0	3	1	0	1	0	23	9	1
244	4	0	1	1	1	0	1	14	6	1
245	0	0	2	2	1	0	0	34	9	3
246	5	0	1	0	1	0	0	9	2	6
247	0	0	0	1	3	0	0	9	9	1
248	2	2	1	3	3	0	0	18	12	5
249	0	2	3	4	3	1	0	15	15	10
250	0	0	3	4	3	0	0	17	16	8
251	0	1	1	1	0	0	0	0	6	2
252	2	0	1	0	0	0	2	21	9	4
253	0	0	1	2	1	0	0	21	5	1
254	0	1	0	3	1	0	0	29	8	9
255	3	0	1	2	0	0	0	11	2	5
256	3	1	6	1	1	1	0	22	11	11
257	1	0	0	4	0	0	0	8	10	1

258	0	1	0	2	1	0	1	16	7	1
259	2	4	0	2	4	0	0	14	4	5
260	1	3	2	7	2	0	0	19	3	4
261	1	0	1	3	1	0	0	2	8	3
262	0	1	2	3	0	0	0	4	9	4