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Forecasting Aviation Spare Parts Demand Using Croston Based Methods and Artificial Neural Networks

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Abstract. Accurate forecasting of spare parts demand not only minimizes inventory cost it also reduces the risk of stock-out. Though we have many techniques to forecast demand, majority of them cannot be applied to spare parts demand forecasting. Spare parts demand data usually have many zeros which makes conventional forecasting methods less effective. In this study we have used latest parametric time series methods and artificial neural networks to forecast spare parts demand of an aviation company. We have shown that with careful selection of the algorithm and their parameters the artificial neural network models give accurate forecasts for spare parts demand. Applying the proposed forecasting methods in aviation maintenance and repair companies will reduce inventory cots and eliminate risks of keeping planes on the ground.

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1. Introduction

Demand forecasting has always been crucial for better inventory planning. Although holding high level inventory reduces the risk of shortages and inefficient operations it constitutes a major portion of the total operating cost. As the need for more efficient operations becomes crucial in modern business environment, more effective forecasting methods are needed. As supply chain management approach starts to dominate the business world, accurate demand forecasting becomes even more desirable.

Nowadays, more demand data are available to be used in forecast than ever. However, not all data are “well behaved”, i.e. smooth type of data. Some of the demand data demonstrate sporadic structure that is characterized by many time periods with zero demands. Though we have many time series forecasting methods to forecast regular demand data, for sporadic demand data the methods are limited. The ongoing research continues for forecasting sporadic demand data. The existing methods can be divided into five categories:

1) Croston based methods: Parametric methods developed from the most popular time series forecasting method ‘exponential smoothing’ (Croston, 1972; Syntetos and Boylan, 2001; Leven and Segerstedt, 2004; Vinh, 2005).
2) Artificial neural network based methods: A radial basis function network (Carmo and Rodrigues, 2004), generalized regression neural network (Amin-Naseri et al., 2007), recurrent neural network (Amin-Naseri and Tabar, 2008), multilayer perceptron (Gutierrez et al., 2008;), hybrid forecasting approach consisting of a multi-layered perceptron neural network (Pour et al., 2008).
3) Support vector machine based methods: (Hua and Zhang, 2006), (Bao et al., 2011)
4) Nonparametric bootstrapping methods: (Willemain et al., 2004), (Snyder et al., 2002).
5) Parametric Monte-Carlo simulation based methods: Integrated forecasting method, (Hua et al., 2006), MCARTA (Rossetti and Varghese, 2008)

The first three categories are focused on point estimates of the demand: try to predict the future value of the demand. The remaining two are focused on interval estimates of the demand: try to predict the future interval (low and high values) of the demand.

In this paper we have forecasted aviation spare parts demand of Turkish Aircraft Maintenance Repair & Overhaul (MRO) company. Like the other examples of spare parts demand majority of demand data series are sporadic. From the five categories of methods we have employed Croston-based methods and artificial neural networks based methods to forecast demand data series since we are focusing on point forecast of the demand. We have compared the performance of Croston-based and artificial neural network methods in terms of accuracy in matching actual demand data with forecasted values. We also have proposed a forecasting method for each demand data type.

In the next section we will introduce categorization of data used for forecasting purposes and then introduce various methods of forecasting used for sporadic data. In Section 4 we introduce our aviation spare part forecasting case followed by results and analysis in Section 5. Section 6 concludes the paper with some concluding remarks and future research.

2. Sporadic Data Categorization

In the literature sporadic demand data were categorized into four types: erratic, lumpy, smooth, and intermittent. When sporadic demand data contain large percentage of zero values, with random non-zero demand data it is called intermittent demand. If the variability of demand size is high, it is called erratic demand. If both variability of demand size and also time periods between successive two nonzero demands are high, it is called lumpy demand. The demand data type is smooth when both variability and time periods between successive two nonzero demands are low.

The categorization scheme is based on the characteristics of demand data that are derived from two parameters: the average inter demand interval (ADI) and the squared coefficient of variation (CV^2). ADI is defined as the average number of time periods between two successive demands which indicates the intermittence of demand,

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

where N indicates the number of periods with non-zero demand and t_i is the interval between two consecutive demands.The CV^2 is defined as the squared of the ratio of the standard deviation of the demand data divided by the average demand which indicates the variability of demand.

$$CV^2 = \sum_{i=1}^{n}(D_i - \overline{D})^2\ (n-1)D2 \qquad (2)$$

where n is the number of periods, and Di and $\bar{D}$ are the actual and average demand in period i, respectively. Syntetos and Boylan (2005) have suggested (ADI = 1.32 and $CV^2 = 0.49$) as cut off values (see Figure1).

Figure 1. Syntetos and Boylan Data Categorization Scheme

$CV^2 > 0.49$	**Erratic**	**Lumpy**
$CV^2 \leq 0.49$	**Smooth**	**Intermittent**
	ADI ≤ 1.32	ADI > 1.32

3. Sporadic Demand Forecasting Methods

Time series methods are commonly used for forecasting regular type of demand data. For sporadic demand (some periods showing no demand at all) special methods should be created with considering the intermittent structure of demand data. Though some methods have already been developed by researchers, in practice usually exponential smoothing method and its variants are used. However they often produce inaccurate forecasts for sporadic demand. The sporadic demand forecasting techniques which are used in this study are following:

3.1. Croston-Based Methods

Croston's paper (1972) on intermittent demand is the pioneering paper that addressed sporadic demand forecasting. He proposed forecasting procedure that independently updates the demand interval between two non-zero demand values and also the demand size. The forecast for the demand per period is then calculated as the ratio of the forecasts for demand size and demand interval.

Croston method is the most frequently used technique for sporadic demand forecasting. In Croston's algorithm, the historical demand is separated into two series: one representing the non-zero demand and the other representing inter-arrival time. The inter-arrival time is identified as the period between two consecutive non-zero demands. Croston method forecasts the non-zero demand size and the inter-arrival time between successive demands using exponential smoothing individually. Both forecasts are updated only after demand occurrences. We consider the following notation:

Y(t) is the estimate of the mean size of a nonzero demand at time t,

P(t) is the estimate of the mean interval between nonzero demands at time t,

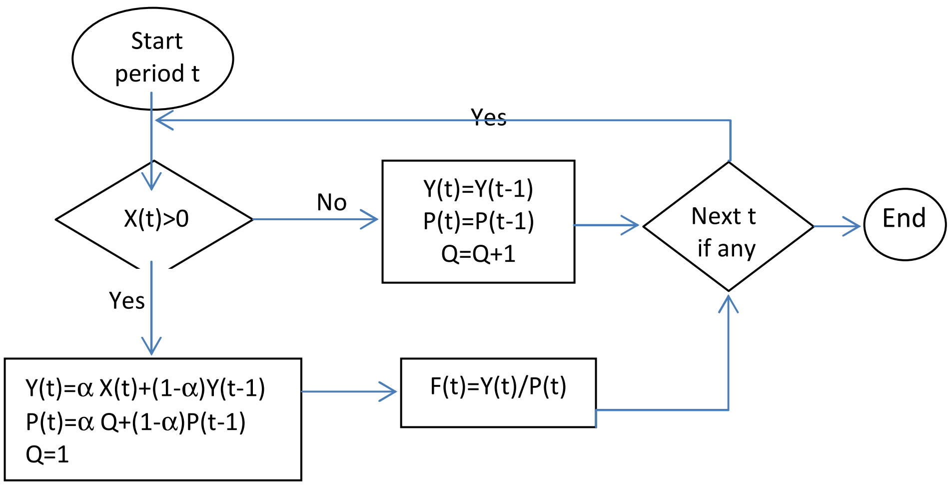
X(t) is the actual demand at time t,

Q is the time interval since the last nonzero demand and

α is the smoothing constant.

Croston forecasting method updates values of Y(t) and P(t) according to the procedure shown in Figure 2.

Figure 2. Croston Method's Algorithm



Croston method finds the forecast of the demand for the period t as follows:

$$Ft = Y(t)P(t) \tag{3}$$

Modifications to Croston method were later developed by other researchers. Syntetos and Boylan (2001) have shown that the initial Croston technique is biased. They have corrected the biasness by multiplying the forecast for the demand per period with $(1-\alpha/2)$ which is defined as the correction factor (Syntetos and Boylan, 2001). If the demand occurs, estimates are updated as the Croston's method. Otherwise, estimates remain same. Their forecast of the demand for the period t is:

$$F(t) = 1 - \alpha 2Y(t)P(t) \tag{4}$$

Levén and Segerstedt (2004) suggested a modification of Croston method to obtain a method that works for both slow and fast moving items. They also aimed to reduce the bias indicated by Syntetos and Boylan. They have updated the forecast of the demand per period using the ratio of demand size and interval rather than individually updating demand size and interval. Their forecast of the demand for the period t is:

$$F(t) = \alpha X(t)Q(t) + 1 - \alpha F(t-1) \tag{5}$$

where X(t) is the size demand at time t and Q(t) is the interval between consecutive demands.

Another variation of Croston method estimates the mean demand per period and mean interval between nonzero demands by applying exponentially weighted average (Vinh, 2005). If the current demand is zero, Y(t) and P(t) values are updated same as the Croston method if the demand is nonzero these values are updated according to following procedure in Figure 3:

Figure 3. Vinh's variation of Croston's method

If $Xt > 0$ then

$$Yt = \alpha Xt + \alpha 1 - \alpha Yt - 1 + 1 - \alpha 2Yt - 2$$

$$Pt = \alpha Q + \alpha 1 - \alpha Pt - 1 + 1 - \alpha 2P(t-2) \tag{6}$$

Like Croston method the forecast of the demand per period t is:

$$Ft = YtPt \tag{7}$$

3.2. Artificial Neural Networks Methods

Another class of Sporadic Demand Forecasting is the Artificial Neural Networks (ANN) method. ANN models are useful for modeling nonlinear relationships between variables. They are robust to outliers and noise. The neural network models consist of multiple inputs and a single output. Main processing ability of a network depends on weights, which multiplies with an input value. The neuron combines these weighted inputs and, with reference to threshold value and activation function, uses these to determine its outputs (Neuralyst User's Guide).

There are three stages in ANN modeling: training, validation and testing. In training phase the relationship between input and output values is being learned. In every iteration, defined error type is being reduced. In cross validation stage, weights of the best solutions are saved. At the end of the training and validation stages, the performance of the model is being measured with new data values.

In forecasting applications of sporadic demand, different types of ANN models like: *Multi-Layered Perceptron* (MLP) method with back-propagation (BP) algorithm which is most commonly used methods in literature was used (Gutierrez, 2008). Besides this, Recurrent Neural Network (RNN) (Amin-Naseri, 2008), Generalized Regression Neural Network (GRNN) (Amin-Naseri, 2007), and some different hybrid methods (Hua, 2006) were used.

Gutierrez et al. have used MLP method and two variables as inputs which are:
1. The demand at the end of the immediately preceding period,
2. The number of periods separating the last two nonzero demand transactions as of the end of the immediately preceding period.

Output was the predicted value of the demand transaction for the current period. They have used 3 hidden units and Back Propagation algorithm. The learning rate value of 0.1 and the momentum factor value of 0.9 were selected.

Amin-Naseri et al. have used RNN method and added two more input variables such as:
1. The number of consecutive period with no demand transaction immediately preceding target period.
2. The mean of demand for four period immediately preceding target periods.

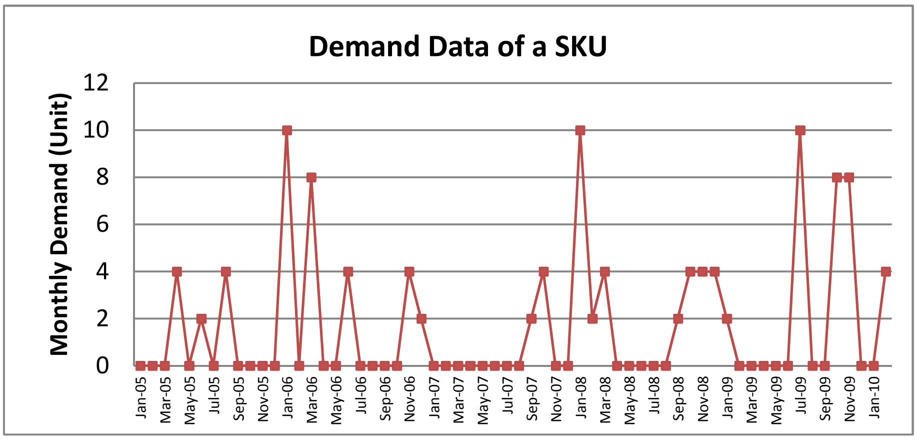
As opposed to back propagation algorithm, in RNN there are no training parameters, such as learning rate and momentum. However, there is a smoothing factor that is used when the network is applied to new data.

In GRNN application, Pour et al.'s network consists of four layers, namely: input layer, hidden layer, a context layer and an output layer. They have added four more input variables to the existing ones:
1. The number of consecutive periods with demand transaction, immediately preceding target period.
2. The number of period(s) between target period and first zero demand immediately preceding target period.
3. The number of period(s) between target period and first nonzero demand immediately preceding target period.
4. The maximum demand among six periods immediately preceding target period.

4. Forecasting Aviation Spare Parts Demand

The dataset we have used in this study is the monthly demand of 90 stock keeping units chosen from the spare parts inventory of Turkish Aircraft Maintenance Repair & Overhaul (MRO) company. The spare parts which had sporadic demand were selected. The demand values cover a period of 62 months from January 2005 to February 2010. The demand data of one item is plotted in Figure 4. This plot is clearly revealing the sporadic behavior of the demand data: the monthly demand has many values of zero. It is also obvious that to forecast such demand series is not easy.

Figure 4. Time plot of monthly demand of one SKU.



The descriptive statistics of the data set is given in Table 1. The average demand size of the demand series are varying a lot. This suggests that some spare parts are fast moving some are slow. Demand interval; “number of time periods between successive nonzero demands”, has an average of more than 1 for all demand series. That means all demand series has some zero demand values, some more and some less.

Table 1: Descriptive statistics of the data set

	Demand Size		Demand Interval	
	Mean	Std. Dev.	Mean	Std. Dev.
Minimum	0,27	0,48	,02	0,13
Lower Quartile	0,60	0,98	,62	1,16
Median	1,46	2,39	,11	1,61
Upper Quartile	3,81	6,28	,96	2,23
Maximum	1734,05	2650,85	,80	5,34

4.1. Aviation Spare Parts Demand Data Categorization

We have categorized the demand data set by using the methodology shown in section 3. The number of demand series from each type and their percentages are given in Table 1. Almost 50 % of the demand series belongs to intermittent type and only 4.4 % is smooth type. This table is confirming that we have a good example of sporadic demand data set. Like spare parts of many industries, spare parts demands of aviation industry are sporadic too.

Table 2: Number and percentages of different type of demand data in each category

Demand Pattern Condition	Demand Type	Number of Data Series	Percentage
ADI≤1.32; CV^2>0.49	Erratic	11	12.2
ADI>1.32; CV^2>0.49	Lumpy	30	33.3
ADI≤1.32; CV^2≤0.49	Smooth	4	4.4
ADI>1,32; CV^2≤0.49	Intermittent	45	50

4.2. Performance Measurement

Measuring the accuracy of the forecasting methods has always been the most important issue in forecasting studies. Though there are many performance measures available in the literature, they are all based on the forecasting error, which is the difference between the actual data and the predicted data values. In this paper we have used 90 different demand series and these series has different mean values, some high some low. Therefore our performance measurement method should not be affected by the magnitude of the different data series. Here, we propose using the Geometric Mean of the Mean Absolute Deviation Average (GMAMAD/A) as a robust performance measure. For each series the mean absolute deviations (MAD) is calculated and divided by the mean of the corresponding series. Then the geometric mean of the resulting scaled MADs are found as follows.

GMAMAD/A = ∏undOvr$i$ = 1N1ni∑undOvr$t$ = 1ni||Xit − Fit∑undOvrt = 1$niXitni$skw1N (8)

where N is the number of data series,

ni is the number of demand time periods which are forecasted, of the i[th] data series,

Xit is the actual demand for the i[th] data series at time t, and

$F\ it$ is the forecast of demand for the i[th] data series at time t.

4.3. Forecasting Demand with Croston based methods

We have applied four Croston based methods namely: Original Croston's method, Syntetos & Boylan approach, Vinh’s approach, and Leven-Segerstedt method. For all methods:

- To initialize the methods: the average of demand values, and intervals between nonzero demands for first 2 years (24 months) were used.
- First 50 data points of demand series were used as training data for each method.
- The smoothing constant alpha of 0.2 was used. In literature for demand forecasting, alpha value between 0.1 and 0.3 was recommended (Silver et al., 1998).
- Finally, the last 12 data points were compared with real observations to measure the performance of each method.

After applying all 4 methods to our data set of 90 series we have calculated GMAMAD/A score for each method. These scores are shown in Table 2.

Table 2: Performance comparisons of forecasting methods based on GMAMAD/A

	Croston	***Syntetos & Boylan***	***Vinh***	***Leven & Segerstedt***
GMAMAD/A	1.588	1.491	1.602	1.161
Rank	*3*	*2*	*4*	*1*

Clearly Leven & Segerstedt performed best in forecasting last 12 months of demand for 90 spare parts. Though it is latest Croston based method Vinh’s variation performed worst. Syntetos and Boylan variation is the second good performer after Leven & Segerstedt.

After finding the best performing method in general a question of which method perform best for each sporadic demand type: intermittent, erratic and lumpy, arises. In here we do not include smooth type as it is less challenging. To answer this question we have evaluated the performance of each method for each non-smooth demand data type. The results are given in Table 3. To our knowledge this is the only study comparing the performances of Croston based methods for each type of sporadic demand.

Table 3: GMAMAD/A results of forecasting methods for each type demand type

	Croston	***Syntetos & Boylan***	***Vinh***	***Leven & Segerstedt***	***Average***
Intermittent	1.805	1.705	.767	**1.279**	1.639
Erratic	0.876	0.834	.083	**0.785**	0.895
Lumpy	1.784	1.647	.748	**1.219**	1.599

For all types of demand series Leven & Segerstedt seems to significantly outperforms all the other three methods. However, the results does not show significant difference in the performance of the other three methods in all types of data. Syntetos & Boylan's performance is the second best but the difference does not seem to be significant from the other two methods. Although these conclusions are limited to the data set used in this study, but they give good indication of the relative performance for other data sets. To confirm this conclusion more data analysis are needed for different types of data sets.

4.4. Forecasting Demand with Artificial Neural Networks

In this study, we have used four different types of ANN models for forecasting sporadic demand data. These models have four different ANN learning algorithms such as: Multilayer Perceptron Network (MLP), Recurrent Neural Network (RNN), Time-Delay Network (TDNN) and Radial Basis Function (RBF) were used. In previous studies MLP and RNN were already used to forecast sporadic demand but to our knowledge this study is the first applying TDNN and RBF algorithms. The reason of applying different ANN algorithms is that each learning algorithm has different computation style. The algorithms are briefly described below.

- MLP are layered feed forward networks that work with back propagation algorithms. It is the most preferred network type because it can approximate any type of input/output values. Disadvantages of these networks are that they train slowly and need many training data than the other networks (NeuroSolutions User's Guide, 1995).
- In Recurrent Neural Network (RNN). There is a directed cycle between neurons. Unlike feed forward networks (i.e. MLP), RNNs have not only feed forward but also feed backward connections between neurons. One another difference of RNN models is that, there is an extra layer –named as context layer- on the structure. Context layer retains the historical data between observations. This property of RNN mostly gives better solutions than the conventional feed forward MLP models. There are different types of RNN models as; fully recurrent network, Hopfield network, Time Delay network etc. The reader is referred to (en.wikipedia.org, 2014) for details of different order picking methods.
- Time Delay Neural Networks (TDNN) is a special case of RNN models. These types of models works on a sequential data. In TDNN models, neurons recognize the features independent of time shift (en.wikipedia.org, 2014). Most of the demand values in our data are zero so this property of TDNN is advantageous for our models.
- RBF networks are different types of hybrid networks that uses both supervised and unsupervised learning methods. There is only one hidden layer. In most of the multi-layer perceptron models standard sigmoidal function is used in this layer. Unlike feed forward networks, RBF networks use Gaussian transfer function. Basically, RBF models are used for proposing approximate multivariate functions by using univariate radial basis functions.

In all of these ANN models we have used nine input variables. The first five input variables were selected from the previous ANN studies (Naseri, et al., 2007; Gutierrez, et. al., 2008; Pour, et al., 2008). The remaining four input variables, we have inspired from Chua's (2008) paper about forecasting lumpy demand. As we only have univariate data (monthly demand values) all inputs are derived from the demand data itself. The following is the brief descriptions of nine input variables:

1. The number of consecutive periods preceding the target period with zero demand,
2. The number of periods separating the last two non-zero demand as of the end of the preceding target period.
3. The number of demand intervals from the last non-zero demand observation until the current period.
4. The maximum demand among six periods preceding target period.
5. The average of demand for six periods preceding target period.
6. pt; is the forecast for the interval between t^{th} and $(t+1)^{th}$ non-zero demand.

$$\mathrm{pt} = \alpha\mathrm{qt} + 1 - \alpha\mathrm{pt} - 1 \tag{11}$$

Where q_t is the interval between the t^{th} and $(t+1)^{th}$ non-zero demand.

7. st; is the forecast of the length of non-zero demand for period t.$\mathrm{st} = \alpha\mathrm{rt} + 1 - \alpha\mathrm{st} - 1$ (12)

Where r_t is the length of non-zero demand for period t.

8. L_t refers to the current level estimate using Brown's exponential smoothing.

$$\mathrm{Lt} = \alpha\mathrm{yt} + 1 - \alpha\mathrm{Lt} - 1 \tag{13}$$

Where, y_t is the t^{th} demand for period t.

9. T_t refers to the current trend estimate using Brown's exponential smoothing.

$$\mathrm{Tt} = \alpha\mathrm{Lt} + 1 - \alpha\mathrm{Tt} - 1 \tag{14}$$

NeuroSolutions 6.0 ANN program is used for all ANN analysis. Primarily, the data set divided into three parts; training data set (first %60 of all data), validation data set (%18 of all data), testing dataset (last %22 of all data). For all ANN models Levenberg-Marquardt (L) and backpropogation (B) is used. After applying all of four methods to our data set of 90 series, we have calculated GMAMAD/A score for each ANN method. The number of hidden layers used was (1 or 2) and the best performing are taken. All of these alternatives are applied in all ANN learning algorithms and GMAMAD/A results of ANN models are as shown in Table 4. As these four defined ANN forecasting models were applied for all of the 90 sporadic demand series we did not show the detailed information: like number of hidden layer, hidden layer neuron number, number of retraining etc. in here.

Clearly Multi-Layer Perceptron (MLP) performed best in forecasting last 12 months of demand for 90 spare parts. Though RNN and TDNN performed the same, RBF performance is the worst among them. Unlike Croston-based models the forecasting performances of these four models are similar to each other.

Table 4: Performance comparisons of ANN forecasting methods based on GMAMAD/A

	RNN	***RBF***	***TDNN***	***MLP***
GMAMAD/A	1.110	1.158	1.111	1.033
Rank	*2*	*4*	3	*1*

A similar performance comparison of ANN forecasting models is done for each sporadic demand type: intermittent, erratic and lumpy. The results are shown in Table 5.

Table 5: GMAMAD/A results of ANN forecasting methods for each type demand type

	RNN	***RBF***	***TDNN***	***MLP***	***Average***
Intermittent	1.124	1.228	1.178	**1.090**	**1.155**
Erratic	1.108	0.995	0.837	**0.786**	**0.932**
Lumpy	1.149	1.186	1.190	**1.107**	**1.158**

In general, the performance of the three methods does not seem to be significantly different. However, among all demand series MLP seems to outperforms the other in intermittent, erratic and lumpy demands. Though RNN is the second good performer for intermittent and lumpy demand types; it is the worst performer for erratic demand type. Like Croston-based models ANN models have forecasted most accurately erratic demand type.

5. Results and Discussions

We have employed both Croston-based and Artificial Neural Networks methods to forecast monthly demand of aviation spare parts. The findings are summarized in Table 6. It is clear that ANN models with newly defined input variables, outperformed Croston-based models. However the performance of Leven & Segerstedt model (Croston-based) is very close to ANN models in performance. If a decision maker is looking for a simpler model with an acceptable performance Leven & Segerstedt is the obvious choice. If the minimum error for predicting the future values is the main objective then ANN's MLP model is the best choice. The results have shown the potential value of ANN for producing accurate forecasts for the decision makers.

Table 6: Performance comparisons of ANN and Croston-based forecasting methods based on GMAMAD/A

	Croston-Based Methods				*ANN Based Methods*			
	Croston	*Syntetos& Boylan*	*Vinh*	*Leven & Segerstedt*	*RNN*	*RBF*	*TDNN*	*MLP*
GMAMADA	1.588	1.491	1.602	1.161	1.110	1.158	1.111	1.033
Rank	*7*	*6*	*8*	*5*	*2*	*4*	*3*	1

Tough ANN methods outperformed the Croston based methods, the performance of a neural network model depends on the two important criteria. The first one is the network architecture that is the number of hidden layers, the number of input nodes in each layer and how the nodes are connected. When the number of hidden layers or number of nodes in the hidden layer is changed, the performance of the ANN analysis may change. The second criterion is the training and testing data set. When the percentage of training and testing data set is changed, performance of the ANN analysis may also change. That's why in real life applications practitioners usually prefer statistical time series methods over ANN for forecasting demands. In our case as Leven & Segerstedt has a close performance to ANN methods we are confident to recommend this method for the users who does not have experience with ANNs.

Our purpose of conducting the categorization of demand types and measuring the performances of each model is to identify the most appropriate forecasting model. Based on the results, we have shown the best performing method for each demand type in Table 7. MLP model of artificial neural networks is the method to forecast when the demand type is intermittent or lumpy. However if the demand type is erratic than Leven & Segerstedt method from Croston models is the best performing method.

Table 7: Best Performing Method According to Demand Types

Demand Type	***Best Performing Method***
Intermittent	ANN's MLP
Erratic	Leven & Segerstedt
Lumpy	ANN's MLP

Lastly we have checked which type of demand is the most difficult to forecast accurately. Table 8 summarizes our findings from previous tables. Both for ANN and Croston based methods, Erratic demand type is easier to predict accurately. Interestingly, though ANN outperforms Croston based methods for forecasting intermittent and lumpy demand, for the erratic data both approaches have similar performance even Croston is slightly better. These results assure that when the demand data is more sporadic, i.e. have more zero values, then ANN becomes a better forecasting tool.

Table 8: Average Scores According to Demand Types

Demand Data Type	***Average of ANN Models***	***Average of Croston Models***
Intermittent	1.155	1.639
Erratic	0.932	0.895
Lumpy	1.158	1.599

6. Conclusions

Managing spare parts inventory is becoming more critical and complicated in modern business environment than ever. One wants to simultaneously reduce inventory costs and insure availability. This classic inventory management dilemma can be eased by accurate demand forecasting. Unfortunately, while demand forecasting is difficult in general, it can be especially difficult to forecast spare parts demand. This is because usually spare parts demands are sporadic. Conventional time series forecasting methods usually perform poorly when applied to sporadic demand. More sophisticated methods are needed to forecast sporadic demand accurately.

In the aircraft MRO industry keeping right amount of spare part inventory is the most critical issue. One aircraft waiting for the spare part for even one day will cost hundred thousands of dollars, whereas keeping huge amount of inventory as many MROs are doing, costs huge amount of opportunity cost. In this paper we have shown that even extreme demand patterns can be forecasted to good degree of accuracy. If the right method can be selected to the demand data the predictions will be close to actual demand. This will not only reduce the inventory amount but also reduce the risk of lack of specific spare part. Discussions about our results with the company's upper management have shown that this research will be extremely beneficial if our proposed forecasting methodology is integrated to their purchasing system.

Although the purpose of this study was to test different forecasting methods for the aviation spare part demand for Turkish Airlines, the research can be further extended to have a general comparative study of forecasting methods for sporadic data. Such extension may involve different data sets followed by detailed statistical analysis. Results can help in choosing best forecasting method for any type of sporadic data regardless of the underlying application.

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