Sādhanā (2020)45:51
https://doi.org/10.1007/s12046-020-1285-8

Intermittent demand forecasting: a guideline for method selection

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MS received 16 January 2015; revised 16 October 2018; accepted 9 January 2020

Abstract. Intermittent demand shows irregular pattern that differentiates it from all other demand types. It is hard to forecasting intermittent demand due to irregular occurrences and demand size variability. Due to this reason, researchers developed ad hoc intermittent demand forecasting methods. Since intermittent demand has peculiar characteristics, it is grouped into categories for better management. In this paper, specialized methods with a focus of method selection for each intermittent demand category are considered. This work simplifies the intermittent demand forecasting and provides guidance to market players by leading the way to method selection based on demand categorization. By doing so, the paper will serve as a useful tool for practitioners to manage intermittent demand more easily.

Keywords. Intermittent demand; demand forecasting; performance measure; Croston's method; method selection.

1. Introduction

Demand has changing behavior in many businesses. In case that a company is not able to predict demand accurately, it is likely that the company will fall behind its competitors in the sector.

Performing intermittent demand forecasting is a hard work due to its nature. A lot of time periods with zero demand and variable demand values at non-zero demand periods are the reasons of poor performance of traditional forecasting methods when applied to intermittent demand. So, it is clear that there is a need for ad hoc intermittent demand forecasting methods.

In this study, specialized forecasting techniques are being handled by making performance comparison of different methods and method selection for different intermittent demand types. The methods considered are: Croston's method which forms a basis for intermittent demand forecasting and the methods developed by Syntetos and Boylan [1], Levén and Segerstedt [2], and Vinh [3] which are variants of the Croston's method.

2. Background

When demand of an item is not smooth and not continuous, it is called "intermittent demand" which does not occur at every forecasting period and has changing values. Intermittent demand is common in service parts, in heavy machinery and electronics, in process industries, in the automotive industry, in spare parts for durable goods, in telecommunication systems, and in service parts for aircraft maintenance Willemain *et al* [4], Hua *et al* [5], Syntetos and Boylan [6], Kalchschmidt *et al* [7], Bartezzaghi *et al* [8], and Ghobbar and Friend [9].

Since intermittent demand has peculiar characteristics, there are a plenty of research for classification of intermittent demand and handling intermittent demand in a simpler way by grouping it into categories. Some intermittent demand categorization schemes are: Williams [10], Johnston *et al* [11], Eaves [12], Ghobbar and Friend [13], Syntetos and Syntetos [14], and Boylan *et al* [15].

A common classification scheme is the one suggested by Syntetos and Boylan [6]. The proposed scheme is based on average demand interval (ADI) and the squared coefficient of variation of demand sizes when demand occurs (CV^2).

Average inter-demand interval (ADI): This parameter is period based which is calculated as average interval time between two demand occurrences.

$$\mathrm{ADI} = \frac{\sum_{i=1}^{N} ti}{N} \tag{1}$$

where t_i is the time period between two consecutive demand periods and N represents the number of all periods.

The squared coefficient of variation (CV^2): This statistical parameter is calculated as standard deviation of the demand divided by the average demand for non-zero

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Published online: 19 February 2020

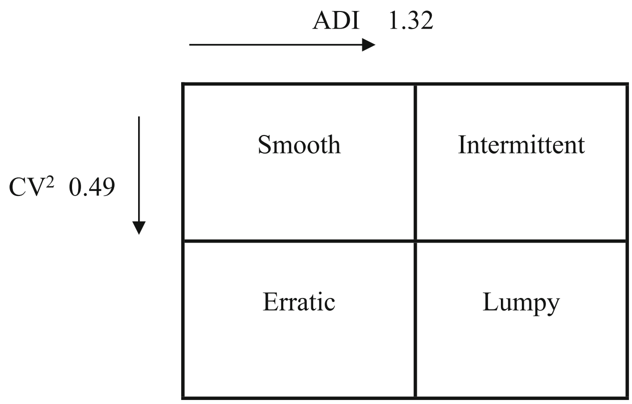

Figure 1. Syntetos *et al*. Categorization Scheme.

demand periods. The squared coefficient of variation represents variability of demand size.

$$\mathrm{CV}^2 = \left[\frac{\sqrt{\frac{\sum_{i=1}^{n}(\varepsilon_i-\varepsilon)^2}{N}}}{\varepsilon}\right]^2 \quad (2)$$

$$\varepsilon = \frac{\sum_{i=1}^{N}\varepsilon i}{N} \quad (3)$$

where N represents the number of periods having non-zero demand, ε_i represents the demand in period, ε represents the average demand considering only periods with non-zero demand (figure 1).

Since traditional forecasting methods assume stationary data, those methods are not able to forecast intermittent demand accurately. Exponential smoothing is shown to mostly results with inappropriate stock levels in the work of Croston [16]. Croston's method modified by Rao [17] is a well-known intermittent demand forecasting technique which inspires many researchers. Rao made several corrections in Rao [17] to algebraic expressions in Croston's paper but those corrections had no effect on the final conclusions or the forecasting procedure.

In his work, Croston uses the non-zero demand size which is represented by Z_t and the inter-demand intervals which is represented by P_t. Two forecasts are performed for demand size and for demand period.

If $Z_t = 0$,

$$\hat{Z}_t = \hat{Z}_{t-1} \text{ and } \hat{P}_t = \hat{P}_{t-1}, \text{ forecast values remain unchanged} \quad (4)$$

If $Z_t \neq 0$,

$$\hat{Z}_t = \alpha Z_t + (1-\alpha)\hat{Z}_{t-1} \quad (5)$$

$$\hat{P}_t = \alpha P_t + (1-\alpha)\hat{P}_{t-1} \quad (6)$$

$$D_t = \frac{\hat{Z}_t}{\hat{P}t} \quad (7)$$

where Z_t: amount of demand in period t, $\hat{Z}_t$: value of demand forecast in period t, α: smoothing parameter (0−1), P_t: time between successive transactions, $\hat{P}_t$: forecast of interval between successive non-zero demand occasions, and D_t: the forecast ofdemand rate.

After the original method, many authors developed variants of the Croston's method by making some adjustments on the method. One of the common variants is the one by Syntetos and Boylan [14]. The new estimator proposed by the authors is

$$D_t = (1-\frac{\alpha}{2})\frac{\hat{Z}t}{\hat{P}t} \quad (8)$$

Syntetos and Boylan [15] measured three forecasting methods on real automotive industry data and their variant showed superior result over other methods.

Another variant is developed by Leven and Segerstedt [2]. The new estimator is as follows:

$$D_t = \alpha\frac{Z_t}{P_t} + (1-\alpha)D_{t-1} \quad (9)$$

Vinh [3] also developed a new variant of Croston's method. In Vinh's variant, the mean demand per period is forecasted by exponentially weighted average method of the two last past values. Vinh's variant is like the original Croston's method but uses the two last past values. The new equations are as follows:

$$\hat{Z}_t = \alpha Z_t + (1-\alpha)\hat{Z}_{t-1} + (1-\alpha)^2\hat{Z}_{t-2} \quad (10)$$

$$\hat{P}_t = \alpha P_t + (1-\alpha)\hat{P}_{t-1} + (1-\alpha)^2\hat{P}_{t-2} \quad (11)$$

The new estimator is found from the same equation as in the original Croston's method. The authors compared their method with the Croston's method and based on the results they concluded that the new variant is more efficient than the Croston's method.

3. Research methodology

For intermittent demand forecasting method selection based on intermittent demand type, we applied Croston's method and its three variants which are Syntetos and Boylan, Leven and Segerstedt, and Vinh methods. The value of smoothing parameter value is important for all these methods since they are all based on simple exponential smoothing method.

In this study, the smoothing constant value is determined to be 0.15 based on other related studies in the literature—Johnston and Boylan [11] and Teunter and Duncan [18]. For the first part of our analysis, we generate artificial intermittent data in order to measure performance of forecasting methods. As described in the background section, there are two main factors for categorizing intermittent demand which are: average inter-demand interval (ADI) and squared coefficient of variation (CV^2). To generate simulated data that fits to each category, we used the following procedure:

- Smooth demand: The condition ADI $\leq$ 1,32; CV2 $\leq$ 0,49 indicates stock keeping units (SKUs) which can be named as fast moving items with demand pattern that does not have any significant raise which does not have inventory control difficulties.
- Intermittent demand: The condition ADI > 1,32; CV2 $\leq$ 0,49 implies low demand patterns with not highly variable demand sizes.
- Erratic demand: The condition ADI $\leq$ 1,32; CV2 > 0,49 indicates items with irregular demand with more repeated demand occurrences.
- Lumpy demand: The condition ADI > 1,32; CV2 > 0,49 indicates items with demand having large differences between non-zero demand values and with a large number of periods between non-zero demand.

Table 1. Levels of the factors for each intermittent demand category.

Category	ADI	CV^2
Smooth	1.05	0.3
Intermittent	5.00	0.3
Erratic	1.05	1.5
Lumpy	5.00	1.5

Table 2. Descriptive statistics of the simulated data set.

Statistics	Demand size	Demand interval
Mean	4.98	3.01
Std. dev.	0.17	1.98
Minimum	4.36	1.03
1. Quartile	4.88	1.05
Median	4.98	2.65
3. Quartile	5.08	4.97
Maximum	5.66	6.05

In order to generate artificial demand data, R software is used. For each category, 100 datasets are generated with 300 data points, i.e. 30,000 data points belongs to each category and 120,000 data points for all. 100 smooth demand series,100 intermittent demand series, 100 erratic demand series and 100 lumpy demand series are generated based on the given factor levels in table 1.

Descriptive statistics of the simulated intermittent dataset are demonstrated in table 2.

In the figures below, simulated intermittent demand examples for the first 100 periods from each demand category (intermittent, lumpy, erratic, and smooth) are demonstrated (figures 2, 3, 4, 5).

Apart from using artificial intermittent demand data, we also use real intermittent demand data. We employ real data of Turkish Airlines service parts during period January 2009 to December 2013. There are 500 stock keeping units (SKUs) in the data set, so there are 131,000 data points totally. According to Syntetos *et al* [15] categorization scheme, considering average inter demand interval and squared coefficient of variation values for spare parts, the data set is categorized as intermittent and lumpy. In Table 3 the distribution of dataset according to demand categories is presented.

Most of data series shows intermittent pattern as can be seen in table 3. Descriptive statistics on Turkish Airlines service parts dataset can be found in table 4.

Geometric Mean of the Mean Square Error Average (GMAMSE/A) proposed by Kaya and Demirel [19] is used as performance measure in this study. The performance metric is calculated as follows:

$$\mathrm{GMAMSE/A} = \left(\prod_{\mathrm{i}=1}^{\mathrm{N}} \left(\frac{{}^{1}/_{\mathrm{n_i}} \sum_{t=1}^{n_i} (D_{it} - F_{it})^2}{\sum_{t=1}^{n_i} {}^{D_{it}}/_{n_i}} \right) \right)^{1/N} \tag{12}$$

where: D_{it} represents the real demand value and F_{it} represents the value of demand forecast for the i^{th} data series at time t, N represents the number of all data series, and n_i represents forecasted number of demand periods of the i^{th} data series.

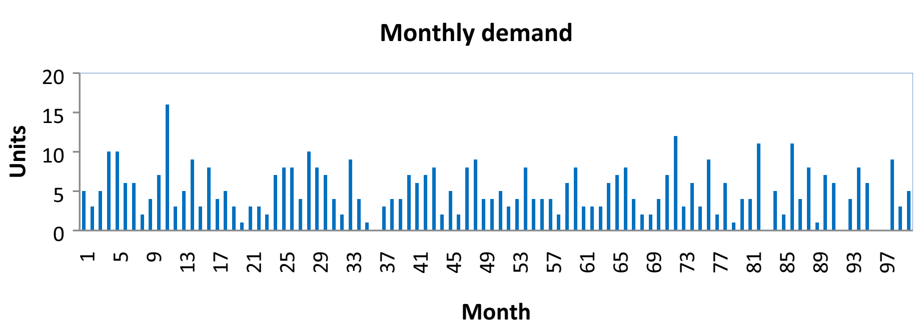

Figure 2. An example of smooth data.

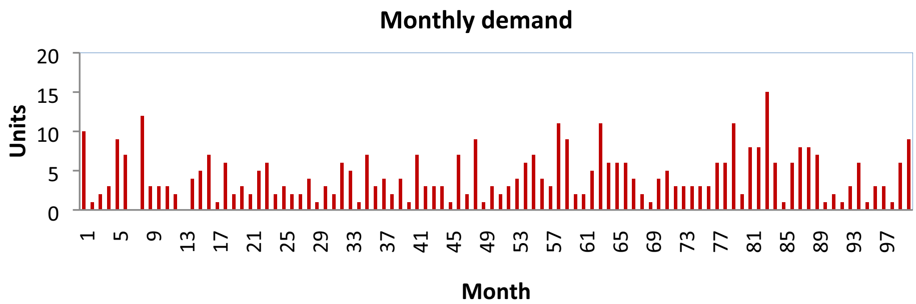

Figure 3. An example of erratic data.

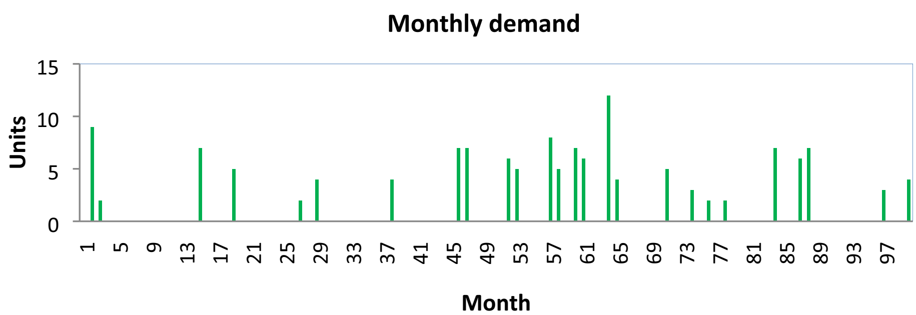

Figure 4. An example of intermittent data.

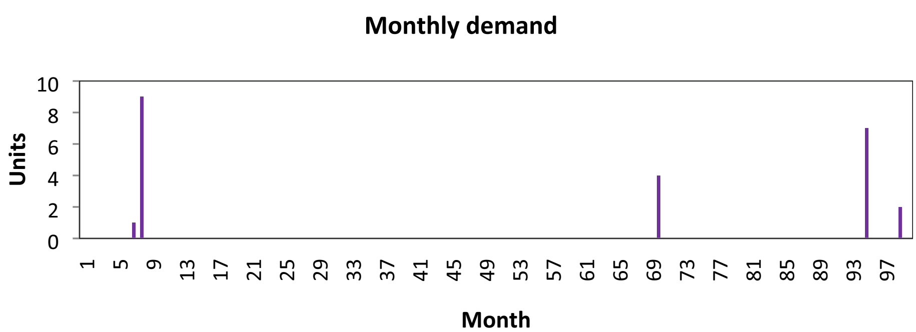

Figure 5. An example of lumpy data.

Table 3. Percentages for each intermittent demand category.

Type	Quantity	Percentage
Intermittent	463	92.6
Lumpy	37	7.4

The steps included in the proposed method selection procedure are represented in figure 6.

Step 1: Croston's method, Syntetos and Boylan's method, Levén and Segerstedt, and Vinh variants of Croston method with smoothing constant value of 0.15 are applied to the data set.

Table 4. Descriptive statistics of the real data set.

Statistics	Demand size	Demand interval
Mean	1.52	31.54
Std. dev.	2.31	54.46
Minimum	1.00	1.00
1. Quartile	1.06	4.31
Median	1.22	10.51
3. Quartile	1.45	28.61
Maximum	49.38	259.00

Step 2: In this step, data is categorized according to Syntetos *et al* categorization scheme considering the

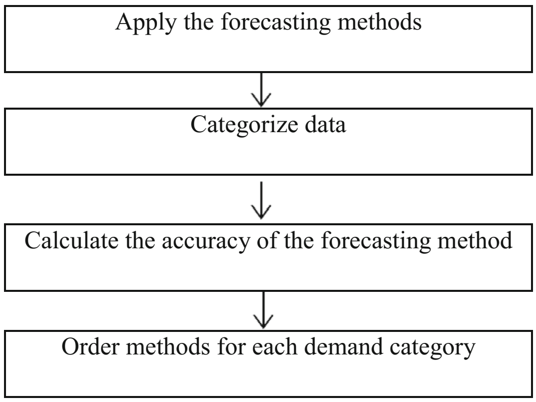

Figure 6. Procedure of method selection.

average inter-demand interval (ADI) and squared coefficient of variation (CV^2) values.

Step 3: For each category, the performances of the methods are evaluated for the data by using Geometric Mean of the Mean Square Error Average (GMAMSE/A).

Step 4: Methods are ordered according to their performances for each demand category.

4. Results

The method selection methodology defined in the previous section is applied both on artificial data and the real data. Intermittent demand forecasting techniques are applied with smoothing constant value of 0.15 which is commonly used value in the literature. Performance results are evaluated for all methods and for all demand types with GMAMSE/A measure. Based on the performance results, order of methods according to their success results is obtained. In the table below, result of the methods for artificial data is presented.

Based on the performance results presented in table 5, we can order methods according to their performances for all demand types. Table 6 is an illustration of methods orders with respect to their performances for intermittent demand type of artificial data.

Table 7 is an illustration of methods orders with respect to their performances for erratic demand type of artificial data.

Table 8 is an illustration of methods orders with respect to their performances for lumpy demand type of artificial data.

Table 9 is an illustration of methods orders with respect to their performances for smooth demand type of artificial data.

In order to compare performance results of artificial data with real data, we applied intermittent demand forecasting methods on real data from aviation sector. Based on the performance results, order of methods according to their success results is obtained. In the table below, result of the methods for real data is presented.

With respect to the performance results presented in table 10, we can order methods according to their performances for all demand types. Table 11 is an illustration of methods orders with respect to their performances for intermittent demand type of real data.

Table 12 is an illustration of methods orders with respect to their performances for erratic demand type of real data.

As can be seen from the tables, results for artificial data and real data are consistent with each other. Order of the method performances are the same for erratic and lumpy demand types in both artificial data and real data.

Based on the results, we can conclude that:

- If demand type is intermittent the order of the methods is Leven and Segerstedt, then Vinh, Syntetos and Boylan and finally Croston. The difference between the best and the least performing methods is huge for intermittent demand type.
- If demand type is erratic the order of the methods is Leven and Segerstedt, then Vinh, Croston and Syntetos and Boylan. However, the performance results are not very different than each other.
- If demand type is lumpy the order of the methods is Leven and Segerstedt, then Vinh, Syntetos and Boylan and Croston. There is a huge performance difference between the best and the least performing methods for intermittent demand type.
- If demand type is smooth the order of the methods is Leven and Segerstedt, then Vinh, Croston and lastly Syntetos and Boylan. However, the performance results are not very different than each other.

Also it is interesting to note that regardless of the demand type, Leven and Segerstedt is the best performing one and Vinh method is the second one.

Table 5. Performance results of forecasting methods for each type demand type.

Category	Croston	Syntetos and Boylan	Vinh	Leven and Segerstedt
Intermittent	20.63	17.90	5.57	5.34
Erratic	2.21	2.22	2.17	2.15
Lumpy	22.28	19.43	6.50	6.24
Smooth	1.43	1.44	1.41	1.36

Table 6. Order of methods according to their performances for intermittent demand type.

Method	Croston	Syntetos and Boylan	Vinh	Leven and Segerstedt
Rank	4	3	2	1

Table 7. Order of methods according to their performances for erratic demand type.

Method	Croston	Syntetos and Boylan	Vinh	Leven & Segerstedt
Rank	3	4	2	1

Table 8. Order of methods according to their performances for lumpy demand type.

Method	Croston	Syntetos and Boylan	Vinh	Leven and Segerstedt
Rank	4	3	2	1

Table 9. Order of methods according to their performances for smooth demand type.

Method	Croston	Syntetos and Boylan	Vinh	Leven and Segerstedt
Rank	3	4	2	1

Table 10. Performance results of forecasting methods for each type demand type.

Category	Croston	Syntetos and Boylan	Vinh	Leven and Segerstedt
Intermittent	2.05	1.91	1.22	1.21
Lumpy	5.04	4.63	3.55	2.73

Table 11. Order of methods according to their performances for intermittent demand type.

Method	Croston	Syntetos and Boylan	Vinh	Leven and Segerstedt
Rank	4	3	2	1

Table 12. Order of methods according to their performances for erratic demand type.

Method	Croston	Syntetos and Boylan	Vinh	Leven and Segerstedt
Rank	4	3	2	1

5. Conclusions

In this research work, intermittent demand forecasting is studied with a focus of selecting proper method with respect to intermittent demand type. Intermittent demand appears sporadically which shows no demand at some time periods. Moreover, it has changing demand values in periods with demand occurrences. These features distinguish intermittent demand from other demand types. Even so, items with intermittent demand structure have considerable amount of the total stock value in most of the sectors, especially those related with spare part.

Demand forecasting is very significant for decision makers since results of demand forecasting have practical effects for the company. All departments plan themselves according to demand forecasts since demand forecast is the prediction of demand values which is the primary source of revenue of a company.

When the item to be forecasted is of intermittent demand type, the forecasting task becomes a difficult issue due to infrequent demand arrivals and variable demand sizes. But since intermittent demand is common in practice, intermittent demand forecasting has critical importance for the corresponding cost savings. Although having low inventory level is desired due to low inventory costs, it can lead to stock-outs which can result with greater cost. For instance, demand forecasting of an aviation sector spare part item with intermittent demand structure is of great importance since absence of a spare part can lead to long down time of the plane. On the other hand, having high inventory levels may lead to unnecessary cost. So, the stock levels should be accurate enough to meet demand as well as low inventory cost.

The fact that items with intermittent demand characteristics constitute a huge portion of total stock value in most of the sectors makes it obvious that intermittent demand forecasting is a significant need for companies and small improvements can lead to substantial cost savings.

On practical side, most practitioners use traditional methods for intermittent demand forecasting purpose which perform poorly. This study is noteworthy for guiding supply chain specialists and showing the way of categorizing intermittent demand. Moreover, since we applied particular intermittent demand forecasting methods, the study has great importance for practitioners to understand that these methods have better performance than traditional methods. By using the guidance of this work, decision makers will be able to categorizing the demand and apply ad hoc intermittent demand forecasting methods and more importantly have the power to select the proper forecasting method for each demand type which makes management of intermittent demand easier.

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