A Hybrid Neural Network and Traditional Approach for Forecasting Lumpy Demand

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Abstract—Accurate demand forecasting is one of the most key issues in inventory management of spare parts. The problem of modeling future consumption becomes especially difficult for lumpy patterns, which characterized by intervals in which there is no demand and, periods with actual demand occurrences with large variation in demand levels. However, many of the forecasting methods may perform poorly when demand for an item is lumpy.

In this study based on the characteristic of lumpy demand patterns of spare parts a hybrid forecasting approach has been developed, which use a multi-layered perceptron neural network and a traditional recursive method for forecasting future demands. In the described approach the multi-layered perceptron are adapted to forecast occurrences of non-zero demands, and then a conventional recursive method is used to estimate the quantity of non-zero demands. In order to evaluate the performance of the proposed approach, their forecasts were compared to those obtained by using Syntetos & Boylan approximation, recently employed multi-layered perceptron neural network, generalized regression neural network and elman recurrent neural network in this area. The models were applied to forecast future demand of spare parts of Arak Petrochemical Company in Iran, using 30 types of real data sets. The results indicate that the forecasts obtained by using our proposed mode are superior to those obtained by using other methods.

Keywords—Lumpy Demand, Neural Network, Forecasting, Hybrid Approach.

I. INTRODUCTION

FORECASTING the future is a critical element of management decision making. The final effectiveness of any decision depends upon the consequence of events following this decision. The ability to forecast the uncontrollable aspects of these events earlier to making the decision should permit an improved choice over that which would otherwise be made [1]. The need for forecasting is increasing as management attempts to decrease its dependence on chance and becomes more scientific in dealing with its environment [2]. Statistical methods, such as exponential smoothing and regression analysis, have been used by analysts

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in forecasting demand for a number of decades. Many of these methods may perform poorly when demand for an item is lumpy. Lumpy demand patterns are characterized by intervals in which there is no demand and, for periods with actual demand occurrences, by a large variation in demand levels [3]. The problem of modeling the future consumption becomes especially difficult for lumpy patterns which are common for the spare parts inventory systems. Forecasting the lumpy demand requires special techniques in comparison with the smooth and continuous case, since the assumptions for continuity and normal demand distribution do not hold [4]. Lumpy demand patterns are very common, particularly in organizations that hold many spare parts. In the aerospace, and automotive sectors, for example, organizations may have thousands or tens of thousands of stock keeping units (SKUs) classified as intermittent or lumpy [5]. For instance, lumpy demand has been observed in the automotive industry [6, 7]; in durable goods spare parts [8], in aircraft maintenance service parts [9], in petrochemical industry [10] and in telecommunication systems, large compressors, and textile machines [3].

Croston [11] implied that traditional forecasting methods such as single exponential smoothing (SES) may lead to sub-optimal stocking decisions and proposed an alternative forecasting method. In proposed procedure, two forecasts for the mean demand-interval and the mean demand-size have been done. The forecast for the demand per period is then calculated as the ratio of the forecasts for demand size and demand interval. Modifications of the original Croston's method were later proposed by several other authors. An important contribution is that by Syntetos and Boylan [6]. They show that Croston's method lead to a biased estimate of demand per unit of time. They also proposed a modified method and demonstrated the improvement in a simulation experiment. Ghobbar and Friend [9] compared various forecasting methods using real data of aircraft maintenance repair parts from an airlines operator. The data is lumpy in nature and they showed that moving average, Holt's and Croston's forecasting methods, are superior to other methods such as the exponential smoothing. Willemain et al. [12] compared various forecasting methods using large industrial data sets. They showed that the bootstrapping method produces more accurate forecasts than both exponential smoothing and Croston's method. In an attempt to develop a forecasting procedure that can handle both fast moving and slow moving items, Levén and Segerstedt [13] proposed a

modification of Croston's method which was thought to avoid the bias indicated by Syntetos and Boylan[6]. Boylan and syntetos [14] reviewed modified Croston procedure to intermittent demand forecasting proposed by Levén and Segerstedt[13]. It has been found to be more biased than Croston's method, especially for highly intermittent series. They assessed the accuracy of this method using simulated data and the mean square error measure, and showed that Croston's method is generally more accurate than its modification, particularly for strongly intermittent series. Eaves and Kingsman [15] compared various forecasting methods using real data from the UK's Royal Air Force. They showed that the modified Croston's method by Syntetos and Boylan is the best forecasting method for spare parts inventory control. Syntetos et al. [16] analyzed a wider range of intermittent demand patterns and made a categorization to guide the selection of forecasting methods. They indicated that there are demand categories that are better used with the original Croston's method and there are others that go well with the Syntetos/&Boylan modification. In an attempt to further confirm the good performance of their modified Croston's method, Syntetos and Boylan [7] carried out a comparison of forecasting methods including theirs and the original Croston's method. A simulation exercise was carried out on 3,000 products from the automotive industry with "fast intermittent" demand. It was shown that the modification is the most accurate estimator. Syntetos and Boylan [17] evaluated the empirical stock control performance of the Syntetos-Boylan approximation (SBA). They first discussed the nature of the empirical demand data set and specified the stock control model to be used for experimentation purposes. Performance measures were then selected to report customer service level and stock volume differences. The out-of-sample empirical comparison results demonstrate the superior stock control performance of the SBA and enable insights to be gained into the empirical utility of the other estimators. Z.S Hua et al. [10] developed a hybrid approach for forecasting the intermittent demand of spare parts. Their approaches provide a mechanism to integrate the demand autocorrelated process and the relationship between explanatory variables and the nonzero demand of spare parts during forecasting occurrences of nonzero demands over lead times. Altay et al. [18] investigated an alternative method developed by Wright in 1986 for data sets with missing values and compared it to a Syntetos-Boylan approximation in a simulated environment.

A little work has been done in lumpy demand forecasting using neural network. Carmo and Rodrigues [19] applied NN modeling on ten "irregularly spaced" time-series. They used a Radial Basis Function (RBF) network. Gaussian basis function networks were shown to be adequate models for short-term prediction of irregularly spaced time series, with the ability to generate better predictive performance than alternative models, by taking into account nonlinear correlations in the data. Gutierrez et al. [20] adopted the most widely used method, a multi-layered perceptron (MLP) trained by a back-propagation (BP) algorithm. Their research

objective was to assess whether the NN-based approach is a superior alternative to traditional approaches for modeling and forecasting lumpy demand.

Amin-Naseri and Rostami Tabar [21, 22] applied generalized regression neural network (GRNN) and Elman recurrent neural network (RNN) for forecasting lumpy demand of spare parts. They showed that neural networks lead to accurate forecasting in comparison to conventional methods.

In this study according to characteristic of spare parts demand a hybrid method (HPM) has been developed for lumpy demand forecasting. In proposed approach, multilayered perceptron neural network ha been used to forecasting occurrence of demand, and then a conventional method used to estimate a quantity of demand. four Statistical accuracy measures showed that our approaches produce more accurate forecasts than traditional method (Syntetos-Boylan Approximation) and recently applied neural network methods like MLP, GRNN and RNN to forecasting lumpy demand patterns.

In the next section, forecasting methods for estimating the lumpy demand problem is reviewed, in the third section, a hybrid proposed approach described. Accuracy measures and characteristics of data are presented in sections four and five. In the sixth section results of our studies are presented. Conclusions are found in the sevenths section.

II. FORECASTING TECHNIQUE

In this section the two most important traditional methods and the recently applied neural network models in forecasting lumpy demand is described.

A. Conventional Methods

Croston [11] developed a method (CR) based on exponential smoothing technique to forecast demand size and demand interval separately. The procedure for Crostone method is described below:

$$if \ \ d_t = 0 \ \ then \ \ \hat{s}_t = \hat{s}_{t-1}, \hat{n}_t = \hat{n}_{t-1} \ \ and \ \ n_t = n_t + 1$$

$$else \tag{1}$$

$$\hat{s}_t = \alpha d_t + (1-\alpha)\hat{s}_{t-n}, \hat{n}_t = \alpha n_t + (1-\alpha)\hat{n}_{t-n} \ \ and \ \ n_t = 1$$

Combining the estimation of size and intervals gives the estimates of mean demand per period.

A disadvantage of the original Croston method is noted by Syntetos and Boylan [6] and Subsequently, Syntetos and Boylan [7] introduced a correction factor of $(1- \alpha)/ 2$, where α is the smoothing constant in use for updating the inter-demand intervals, to arrive at a modified demand forecast. In this study widely range of smoothing constants from 0.05 to 0.45 with increments 0.05 have been used for Croston's method and Syntetos-Boylan approximation (SBA).

B. Multi-Layered Perceptron

Gutierrez et al. [20] adopted the most widely used method, multi-layered perceptron (MLP) trained by back-propagation (BP) algorithm for lumpy demand forecasting. They used

three layers of MLP: the input layer for input variables, hidden unit layer, and output layer. The MLP had three nodes in the hidden layer. One output unit was used in the output layer. The input nodes represent two variables; i) the demand at the end of the immediately preceding period and, ii) the number of periods separating the last two nonzero demand transactions as of the end of the immediately preceding period. The output node represents the predicted value of the demand transaction for the current period. They used a learning rate value of 0.1 and momentum factor value of 0.9 [20].
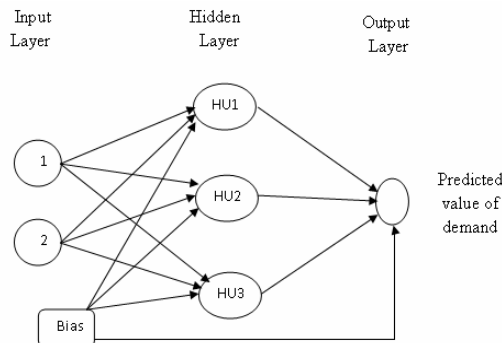

Fig. 1 Schematic diagram of MLP applied by Gutierrez et al

C. Generalized Regression Neural Network

Generalized Regression Neural Network (GRNN) proposed by Spetch [23] does not require an iterative training procedure as in back propagation method.

The GRNN consists of four layers: the input layer, pattern layer, summation layer and output layer. Schematic diagram of GRNN architecture is presented in Fig. 2 [23].

Amin-naseri et al. [21] have been applied GRNN in modeling lumpy demand. They used a four input nodes in input layer and in this model smoothing parameter, σ from 0 to 50 have been tested. The following input variables have been defined in the GRNN:

1. The demand at the end of the immediately preceding target period (lag 1).
2. The number of consecutive period with no demand transaction immediately preceding target period.
3. The number of periods separating the last two nonzero demand transactions as of the end of the immediately preceding target period.
4. The mean of demand for four period immediately preceding target periods.
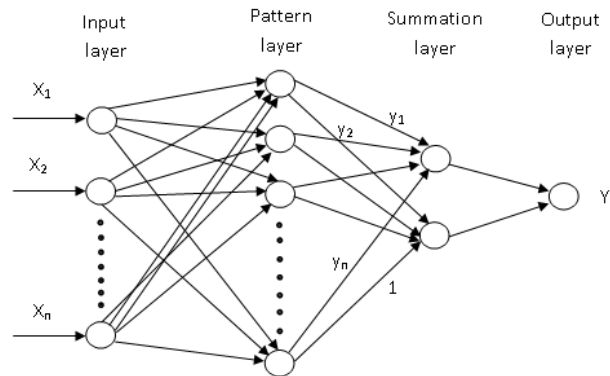

Fig. 2 Schematic diagram of GRNN architecture

D. Recurrent Neural Network

Amin-Naseri & Rostami Tabar [22] adapted recurrent neural network (RNN) to forecasting lumpy demand of spare parts. They used the basic Elman-type RNN [24] also referred to as the globally connected RNN. The network consists of four layers (Fig. 3): an input layer, a hidden layer, a context layer and an output layer [14].

In this network, following variables have been defined for input nodes in input layer:

1. The demand at the end of the immediately preceding target period (lag 1).
2. The number of consecutive periods with demand transaction, immediately preceding target period.
3. The number of consecutive period with no demand transaction, immediately preceding target period.
4. The number of periods separating the last two nonzero demand transactions as of the end of the immediately preceding target period.
5. The number of period(s) between target period and first nonzero demand immediately preceding target period.
6. The number of period(s) between target period and first zero demand immediately preceding target period.
7. The mean of demand for six periods immediately preceding target period.
8. The maximum demand among six periods immediately preceding target period.

In this study tan-sigmoid and saturated linear (satlins) transfer functions, have been used in hidden and output layers, respectively. Thus, according to the following formula data scaled to (-1, 1):

$$S_i(scaled) = \left[\frac{S_i - \min(S)}{\max(S) - \min(S)}\right] \times 2 - 1 \qquad (2)$$

where S is the time series of variable under consideration, S_i is the value of observations and $S_i(scaled)$ is the normalized value. To find the best number of neurons in the hidden layer, range of 1 to 15 neurons have been examined and one with minimum error were selected. When an input is presented to the network the training algorithm (learning equation)

attempts to adjust the weights so that the desired output is produced. In this research back propagation algorithm have been used as training algorithm with learning rate of 0.01. The adjusting parameters of network have been specified using adaptive calibration algorithm. Because of limited historical data this algorithm preferred to batch mode training for training process.
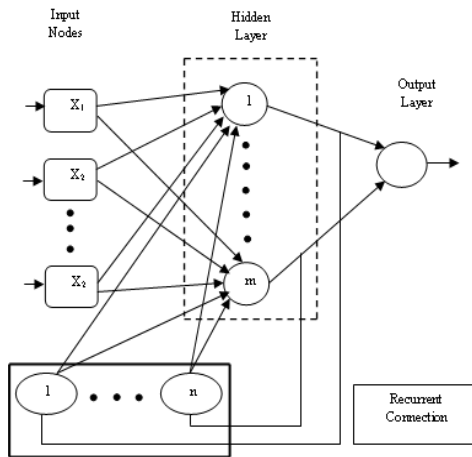

Fig. 3 Schematic diagram of Elman type RNN architecture

III. HYBRID PROPOSED APPROACH

In this study a hybrid approach has been adopted for forecasting the future demand of spare parts. Based on the characteristic of spare parts demand, demand time series contain a large proportion of zero values and for periods with non-zero demand high variability among the non-zero values has been observed. This property implied that forecasting accuracy of occurrence of non-zero demand is more important than that of quantity of non-zero demands for lumpy demand patterns. In this research, firstly, we a neural network model to forecast the occurrence of non-zero demands has been developed, then according to results of neural network model and using a recursive method a quantity of non-zero demand has been estimated.

A. Forecasting Occurance of Non-Zero Demand

Let d_t be the observed demand in period t(t=1,2,3,...n). to forecast the occurrence of non-zero demand, we have to transform the demand time series $\{d_1, d_2,..., d_n\}$ into a binary time series in which 0 represents zero demand and 1 represents non-zero demand. Therefore we use the binary time series demand to forecasting occurrence of demand.

In this study a multi layered perceptron (MLP) neural network has been used for forecasting occurrence of demands. We used three layers of MLP: one input layer, one hidden layer and one output layer. To find the best number of neurons in the hidden layer, range of 1 to 15 neurons have been examined and the best one was selected. The tan-sigmoid and positive linear transfer function used in hidden and output

layer, respectively. In this model back propagation algorithm have been used as training algorithm with learning rate of 0.01 and adjusting parameters of network have been specified using adaptive calibration algorithm. Because of limited historical data this algorithm preferred to batch mode training for training process. The input nodes in input layer have been defined as follows:

1. The demand at the end of the immediately preceding target period (lag 1).
2. The number of periods separating the last two nonzero demand transactions as of the end of the immediately preceding target period.
3. The number of period(s) between target period and first nonzero demand immediately preceding target period.
4. The number of period(s) between target period and first zero demand immediately preceding target period.

According to the output layer transfer function, the output nod represents the predicted values for occurrence of demands. If the predicted value is equal to zero then the current period hasn't any demand, but if predicted value is more than zero we converted it to 1, therefore it has a demand and quantity of non-zero demand has been computed using a conventional recursive method.

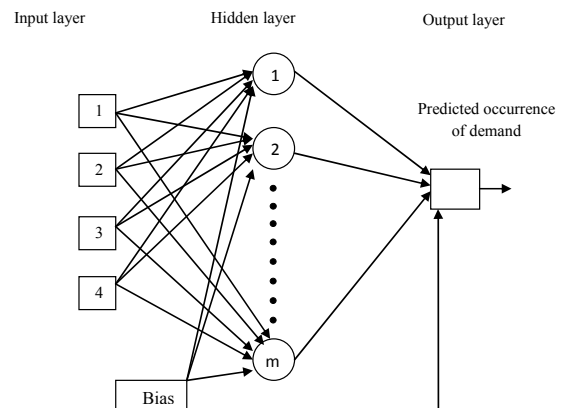#### B. Estimation Amount of Non-Zero Demand

Fig. 4 Schematic diagram of MLP used in hybrid approach

When occurrences of non-zero demands have been forecasted, we need to give the specific numerical values to the non-zero forecasts. In this study we use a conventional method to make the hybrid method. In order to find the best conventional method to use with neural network, first of all, we considered ability of all traditional methods in lumpy demand forecasting to compound with neural network models. Croston's method and combinations of this method could not be used, because in these methods we have to forecast size and interval between demands for all periods, whereas in hybrid approach we need a method to forecast quantity of only nonzero periods.

In this research according to the characteristic of

exponential smoothing, a variation of this method has been used as a conventional recursive method. This method is defined as following:

$$\hat{F}_C = \alpha D_P + (1 - \alpha)\hat{F}_P \qquad (3)$$

Where

$\hat{F}_t$: Forecasting of the current non-zero period

D_P : Actual demand of previous non-zero period

$\hat{F}_t$: Forecasting of the previous non-zero period

In the other hand, in this method after forecasting of nonzero demands using neural network, firstly we filter all periods with non-zero demands then apply exponential smoothing to these periods. In this method similar to single exponential smoothing, α is the smoothing parameter. In this study range of smoothing constants from 0.05 to 0.9 with increments 0.05 has been used. Fig. 5 shows steps of hybrid proposed method (HPM) in this study.
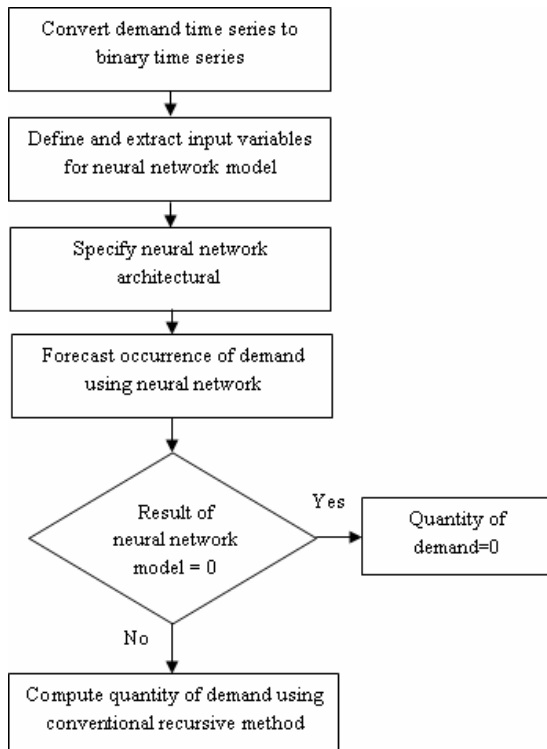

Fig. 5 Flowchart of hybrid proposed method

IV. STATISTICAL ACCURACY MEASURE

To compare the performance of the methods under consideration, three error measures have been considered which will be introduced as follows. The scaled error q_t, at time t is calculated using (4):

$$q_t = \frac{e_t}{\frac{1}{n-1}\sum_{i=2}^{n}(d_i - d_{i-1})} \qquad (4)$$

And MASE is then the average of absolute values of q_t [25].

Hoover [26] has suggested many variations on the MAPE, among which the ratio of MAD to MEAN which we call as adjusted MAPE (A-MAPE) has been used in this study.

$$A - MAPE = \frac{\frac{\sum_{i=1}^{n}|d_i - f_t|}{n}}{\frac{\sum_{i=1}^{n}d_i}{n}} \qquad (5)$$

The third error measure is the percentage best for m existing methods (PB_m). The mathematical expression for this method is:

$$PB_m = \left(\frac{\left(\sum_{t=1}^{n}B_{m,t}\right)}{n}\right) \times 100 \qquad (6)$$

Where, for time period t, $B_{m,t} = 1$ if $|d_{m,t} - f_{m,t}|$ is the minimum of $|d_{k,t} - f_{k,t}|$ for all methods k under consideration and $B_{m,t} = 0$ otherwise [7].

The last measure that we consider in this study is Geometric Mean (across series) of the Arithmetic Mean (across time) of the Absolute Errors (*GMAMAE*):

$$GMAMAE = \left(\prod_{i=1}^{N}\left(\frac{1}{n_i}\sum_{t=1}^{n_t}|Y_{it} - \hat{Y}_{it}|\right)\right)^{1/N} \qquad (7)$$

The measure is also robust to occasional large forecast errors, provided the remaining errors are stable, and are not unduly affected by trend or seasonality. It can therefore be recommended for application in these cases [27].

V. INDUSTRIAL DATA

In this study real data sets of 30 types of spare parts demand in Arak petrochemical enterprise in Iran have been used. The data were gathered from Arak petrochemical company's inventory control software package. The data were handled for 69 monthly periods from 2001 to 2006. Average inter-demand interval (ADI) and squared coefficient of variation (CV^2) measures were used to classify demand patterns into four categories. The demand patterns is classified into lumpy demand category when the average inter-demand interval (ADI) is greater than 1.32 and squared coefficient of variation (CV^2) is greater than 0.49. The data series were divided into two sets; namely training and test sets. From 67 monthly observations, 55 observations have been used for training the networks, and all methods tested using the last 12 observations. For Croston's method and Syntetos-Boylan approximation (SBA) data series have been divided into three blocks: (i) initialization, (ii) calibration and (iii) performance measurement. The lengths of these blocks are 12- 43-12.

The 'initialization block' is used to initialize value required for methods based on recursive formulae. In the 'calibration block', the optimal smoothing constants are identified, based on MSE. Finally, the optimal smoothing constants are used to update forecasts in the 'performance block', in which performance statistics are calculated.

VI. EMPIRICAL RESULT

Table I reports adjusted MAPE for the methods under consideration. As can be seen in this Table, a simple average of 30 A-MAPEs for HPM is 26.86, while this measure for method RNN is 30.85, for GRNN is 42.08, for MLP is 48.31 and for SBA is 49.95, which clearly proves the superiority of our hybrid proposed method.

TABLE I
A-MAPEs OF DIFFERENT FORECASTING METHODS

Series	SBA	MLP	GRNN	RNN	HPM
1	3.09	1.73	3.26	1.40	0.95
2	0.98	0.89	0.87	0.86	0.95
3	0.87	1.11	1.04	1.09	0.61
4	0.71	0.96	0.74	0.61	0.51
5	0.82	0.89	0.89	0.65	0.76
6	1.09	1.18	1.09	1.02	1.09
7	1.30	1.16	1.76	1.11	0.60
8	0.96	1.14	1.80	1.20	0.78
9	3.84	5.91	2.92	0.81	1.27
10	2.36	1.37	1.03	1.13	0.55
11	1.01	1.00	1.08	0.94	1.23
12	1.58	2.48	0.65	0.75	1.00
13	0.78	0.85	0.70	0.75	0.73
14	1.65	0.91	0.74	0.83	0.56
15	1.10	1.02	1.00	0.95	1.19
16	0.53	0.83	0.52	0.54	0.60
17	1.49	1.45	1.29	1.28	1.26
18	0.97	0.98	0.96	0.88	1.07
19	1.59	1.44	1.43	1.48	0.10
20	2.36	1.64	1.84	1.17	0.99
21	1.14	1.00	1.00	0.97	0.83
22	1.45	1.13	1.07	1.13	1.50
23	1.92	1.29	1.31	1.64	1.72
24	4.06	3.77	2.29	0.51	1.33
25	1.72	2.96	3.04	1.30	0.20
26	1.59	1.73	1.41	1.25	0.96
27	2.03	2.83	0.92	1.65	1.25
28	1.33	1.17	1.09	1.10	0.44
29	1.10	0.94	0.97	0.86	0.96
30	4.54	2.55	3.40	0.97	0.88
Average	**49.95**	**48.31**	**42.08**	**30.85**	**26.86**

Table II indicates GMAMAE for five methods under consideration. The GMAMAE for HPM is 90.5, for RNN is 115.1, for GRNN is 150.9, for MLP is 108.8 and for SBA is 140.7. As the table shows hybrid approach has a better performance than those other methods.

TABLE II
GMAMAEs OF DIFFERENT FORECASTING METHODS

SBA	MLP	GRNN	RNN	HPM
140.7	108.8	150.9	115.1	90.5

Table III shows performance of the methods considering the MASE error measure. As can bee seen in this Table a simple average of 30 MASEs for HPM is 20.86. While this measure for method RNN is 23.68, for GRNN is 30.79, for MLP is 34.92 and for SBA is 36.21, which indicate the superiority of the HPM method.

TABLE III
MASEs OF DIFFERENT FORECASTING METHODS

Series	SBA	MLP	GRNN	RNN	HPM
1	1.42	0.79	1.49	0.64	0.43
2	0.69	0.63	0.62	0.61	0.68
3	0.57	0.73	0.68	0.71	0.40
4	0.75	1.00	0.77	0.64	0.53
5	0.92	1.01	1.00	0.73	0.86
6	0.80	0.87	0.80	0.75	0.75
7	1.31	1.17	1.78	1.12	0.60
8	1.21	1.44	2.27	1.51	0.99
9	2.02	3.11	1.53	0.42	0.67
10	1.44	0.84	0.63	0.69	0.34
11	0.95	0.94	1.01	0.88	1.15
12	1.45	2.27	0.59	0.69	0.92
13	0.79	0.87	0.70	0.76	0.74
14	1.90	1.05	0.85	0.96	0.64
15	0.77	0.72	0.71	0.67	0.83
16	0.64	1.00	0.62	0.65	0.73
17	1.12	1.08	0.96	0.96	0.95
18	0.72	0.73	0.71	0.65	0.79
19	0.73	0.66	0.66	0.68	0.04
20	1.08	0.75	0.84	0.54	0.46
21	1.74	1.53	1.53	1.48	1.26
22	0.76	0.59	0.55	0.59	0.78
23	1.45	0.97	0.99	1.23	1.29
24	2.22	2.06	1.25	0.28	0.73
25	0.79	1.36	1.39	0.60	0.09
26	0.92	1.01	0.82	0.73	0.56
27	1.49	2.07	0.68	1.21	0.92
28	1.06	0.94	0.88	0.89	0.36
29	0.76	0.65	0.67	0.60	0.67
30	3.75	2.11	2.80	0.80	0.72
Average	**36.21**	**34.92**	**30.79**	**23.68**	**20.86**

TABLE IV
PB STATISTICS FOR DIFFERENT FORECASTING METHODS

Series	SBA	RNN	HPM
1	16.67	16.67	66.67
2	25	33.33	41.67
3	46	30	24
4	8.33	33.33	58.33
5	0	25	75
6	8.33	33.33	58.33
7	25	20	55
8	62.67	16.67	20.67
9	0	0	100
10	8.33	16.67	75
11	14.67	25	60.33
12	8.33	8.33	83.33
13	33.33	21	45.67
14	25	33.33	41.67
15	10	25	65
16	29.33	10	60.67
17	41.67	8.33	50
18	33.33	8.33	58.33
19	0	0	100
20	16.67	16.67	66.67
21	25	33.33	41.67
22	16.67	41.67	41.67
23	16.67	39.67	43.67
24	0	8.33	83.33
25	0	8.33	91.67
26	0	25	75
27	16.67	16.67	66.67
28	8.33	16.67	50
29	25	27.33	47.67
30	0	25	75
Average	**17.56%**	**21.00%**	**61.44%**

Table IV reports the model performance based on percentage best statistic (PB). These PB statistics further establish the overall superiority of HPM approaches (averaging 61.44 for HPM vs. 21 for RNN and 17.56 for SBA). Given the superiority of SBA over Croston's method, we dropped the latter method from analysis.

VII. CONCLUSION

Accurate lumpy demand forecasting of spare parts is importance in inventory management. Owing to demand characteristics of spare parts, demand forecasting in this area is especially difficult. Time series of spare parts demand includes large proportion of zero values; therefore forecasting the occurrences of demands is more important than a quantity of demands.

In this study, based on nature of spare parts demand, a hybrid approach has been developed for lumpy demand forecasting. In hybrid proposed method, multilayered perceptron neural network used to forecasting occurrence of demands, and then the conventional recursive method used to estimate the quantity of demands. The proposed model has been applied to forecast the future demands of spare parts of Arak Petrochemical Company in Iran based on the historical demand data sets of 30 types of spare parts. To evaluate the performance of the proposed model four competing methods, namely Syntetos & Boylan approximation, MLP, GRNN and RNN were applied for forecasting purposes by using the same data set. Results show that our model generally performs better than other forecasting methods using four different forecast performance measures. Because of the capability of neural network methods in forecasting of occurrences and the quantity of demands, Future interesting issue is the possibility of combining neural network models to build a hybrid approache for forecasting future demands of spare parts.

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