

Intermittent demand forecasting by using Neural Network with simulated data

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Abstract

Recently, with unusual changing occurred occasionally in the global market, the manufactures are facing with one of big issues is prediction of the intermittent demand of products. Utilizing available information to estimate as well as possible the “lumpy demand” will be the key for success in supply chain management. Even though a number of tools were developed for such situations in literature, there are rooms for improvement. In this paper, a comparative study is performed with simulated data to show that the neural network can be a promising tool to conventional Croston methods for predicting intermittent demand in term of two criteria mean squared error (MSE) and mean absolute error (MAE). It is, to the best of our knowledge, using simulated data for validating the efficiency of the proposed approach in the general cases is the first such attempt.

Keywords

Intermittent demand, neural network, Croston methods, supply chain management

1. Introduction

It is obvious that intermittent demand forecasting plays a crucial role in manufacturing and inventory management. Intermittent demand or “lumpy demand” that happens at infrequent, irregular and often unpredictable in both intervals and quantities is characterized by intervals in which there is no demand. This kind of demand exists in both manufacturing and service environments. The data of these irregular demands are appeared as time series of zero-demands and nonzero-demands that make them much more difficult to be predicted compare to conventional time series data.

There are number of works have been noted in literature that focused on the application of neural network (NN) model in intermittent demand forecasting. In 2004, Carmo and Rodrigues have applied NN model on “irregular spaced” time series [1]. From another aspect, using nine large industrial datasets of intermittent demands, Willemain T. R., et. al., 2004 show that the bootstrapping method can be produced more accurate forecasts of the distribution of demand over a fixed lead time than do exponential smoothing and Croston’s method [2]. For intermittent demand forecasting, Gutierrez R. S. et utilized multi-layered perceptron (MLP) NN model and compared its efficiency with conventional method’s in 2008 [3]. In the field of critical spare parts, which naturally have the characteristic of more expensive, larger demand variation, longer purchasing lead time than non-critical spare parts, Chen et. al., 2010 tried to apply moving back-propagation neural network (MBPN) and moving fuzzy-neuron network (MFNN) to effectively predict their requirement [4]. In aspect of NN, it is clear that the structure of neurons and their network configuration are most important factors that fundamentally affect on the efficiency of NNs as well as their predictable capabilities. As a continuous contribution to this research branch, the aim of this paper is attempt to utilize the feed-forward back propagation network as an alternative potential tool to conventional methods for predicting intermittent demand. To illustrate that proposed NN model can perform better results of intermittent demand forecasting, random intermittent time series data sets are generated for both training and validating steps. Also, a comparison study between proposed method and well-known Croston’s method is conducted with two criteria such as mean squared error (MSE) and mean absolutely error (MAE).

2. Forecasting methods and data

2.1 Conventional method

In this paper, the conventional Croston method with two values of alpha is used for comparison. There are two main steps. First, the mean demand data per period are calculated by separately applying exponential smoothing. Second, the mean intervals between demands are calculated. Then, they are used in a form of the model to predict the future demands.

2.2 Neural network models

Methodologically, modeling can be classified into two principles: “white box” and “black box”. While the white box principle bases on the knowledge on the phenomenon and the all perceived relationship between inputs and outputs can be represented by mathematical equations, the black box principle do not required any knowledge about the input – output relationships, especially when those relationships are too complex or cannot understandable.

In time series data modeling, conventional models often base on autocorrelation analysis. In the case of intermittent demand, it is seem that autocorrelation analysis based models do not work well. It is difficult to find the auto-correlative relationship so that the forecasting is not an easy issue. To fit such kind of problem, NN can be a potential candidate tool. Principally, NN is a typical stochastic model based on black box approach. NN is an interconnected group of neurons or a network of neurons that uses a mathematical or computational model for information processing. In NN, each neuron is a unit of computation in which a simple mathematical model is used. Hence, a NN based on a connective approach will possessed a powerful computational capability. A typical neural network is illustrated in following Figure 1:

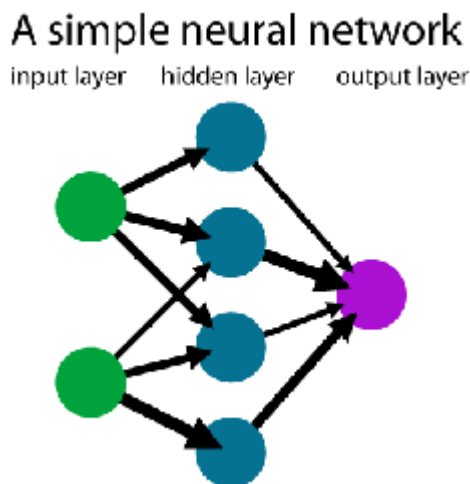


Figure 1: A typical neural network (reprinted from Wikipedia.org)

In most cases, a NN is an adaptive system that can change its structure based on external or internal information flow through the network. In other word, based on the input and output data sets, the NN will repeatedly change the weights and biases in neuron units so that it can represent a complex function between output and input factors. This process is called training or learning in which NN can “learn” or “be trained” to “understand” the complicated relationships between input and output factors. The following Figure 2 shows the mathematical structure of a typical neuron.

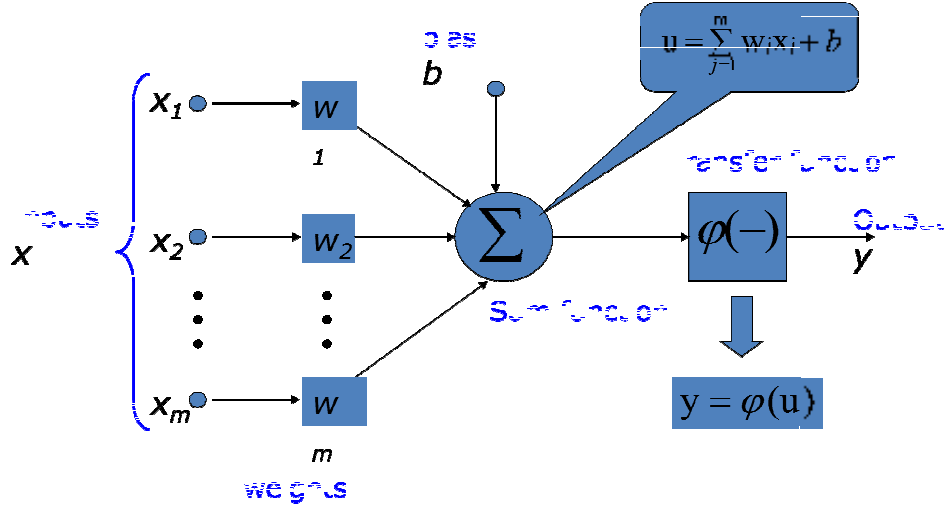


Figure 2: Mathematical structure of typical neuron

There are many kinds of transfer functions available for utilizing in NN, one of most common function is logsig function can be showed in below figure:

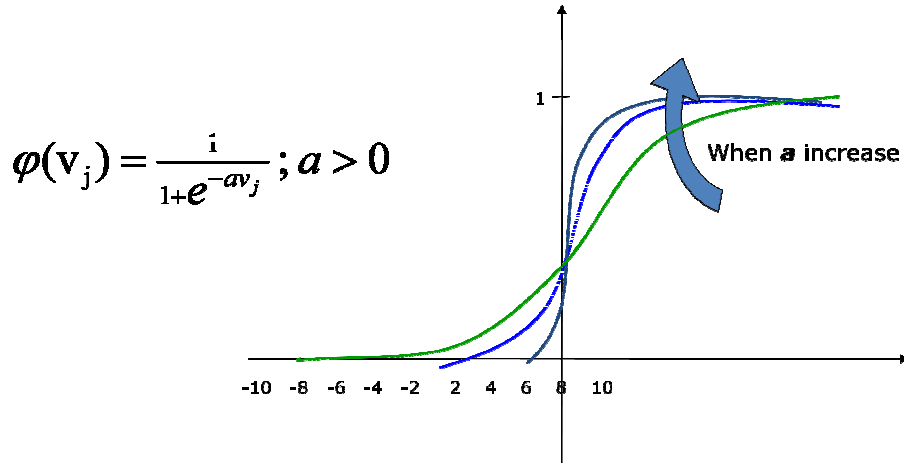


Figure 3: A typical transfer function: logsig function

2.3 Data generation

For comparative study, two data sets (training set and validating set) of intermittent demands are generated randomly. Intermittent time series data can be separated into two parts: non-zero demands (non-zero demand series) and the interval between two non-zero demands (zero interval series). In each data set (training or validating data set), these two subsets of data are generated randomly first, then integrated into one series. In training data set, for the non-zero demands series, 200 integer data are generated randomly from 4 to 15. For zero interval series, 200 data are generated randomly based on geometric distribution. As a result, about 1000 intermittent data in time series are used for training. Similarly, 60 integer data and 60 geometric distributed data are generated independently in the same way for validating set. Therefore, about 300 intermittent data in time series can be used for validating step.

2.4 Error estimation

For evaluating the efficiency of proposed approach as well as comparing two predicting approaches, two criteria are used: mean squared error (MSE) and mean absolute error (MAE). MSE can be calculated by following formula:

$$MSE = \sum_{i=1}^n \frac{(e_i)^2}{n} = \sum_{i=1}^n \frac{(d_i - p_i)^2}{n} \quad (1)$$

in which e_i is the deviation between the observed demand d_i and the predicted demand p_i at the time i , n is the number of data in series.

Also, MAE can be estimated by:

$$MAE = \sum_{i=1}^n \frac{|e_i|}{n} = \sum_{i=1}^n \frac{|d_i - p_i|}{n} \quad (2)$$

3. Results and analysis

The following table shows comparative results of two methods used for predicting the simulated intermittent data. There are 10 pairs of intermittent series data sets for training and validating are generated and ran with both Croston and proposed NN method. MSE and MAE criteria are used for comparing their predicting capabilities. About 1000 intermittent data in time series date sets are used for training and 300 for validating. With Croston method, two value of alpha 0.3 and 0.5 are considered.

Table 1: Comparative results

Series	N training	N validating	Croston alpha = 0.3		Croston alpha = 0.5		Neural network	
			MSE	MAE	MSE	MAE	MSE	MAE
1	889	256	17.16518	3.213056	17.39775	3.294777	1.298526	0.414687
2	1032	277	16.94134	3.113991	17.24845	3.179816	1.567149	0.440975
3	1053	317	18.01292	3.1976	18.80318	3.327096	1.327688	0.363257
4	977	297	19.09358	3.37889	21.13574	3.682611	1.003908	0.319835
5	1047	310	15.27456	2.884753	17.05877	3.133223	1.15634	0.352136
6	956	267	18.02794	3.296088	18.09121	3.334309	1.580755	0.465035
7	1004	294	15.82756	2.966491	15.87653	3.028191	1.403137	0.399225
8	975	320	17.55667	3.096869	18.53241	3.324484	1.242466	0.348748
9	1006	304	16.46479	2.895371	17.1026	3.03908	1.32647	0.361926
10	936	260	17.06976	3.273359	17.91836	3.379255	0.933998	0.333894

Arbitrary, the results of series 10 can be selected to display in following figures. In the Figure 4, the blue bars is the intermittent demand observations from time =1 to time = 936. The red colored circles are the trained values with selected NN model. In the Figure 5, a set of 260 time series data for validating is showed. Similar to figure 4, blue bars and red colored circles represent observed demand and predicted values respectively. Also, Croston method with alpha = 0.3 and alpha = 0.5 are displayed by cyan color line and magenta color line, respectively.

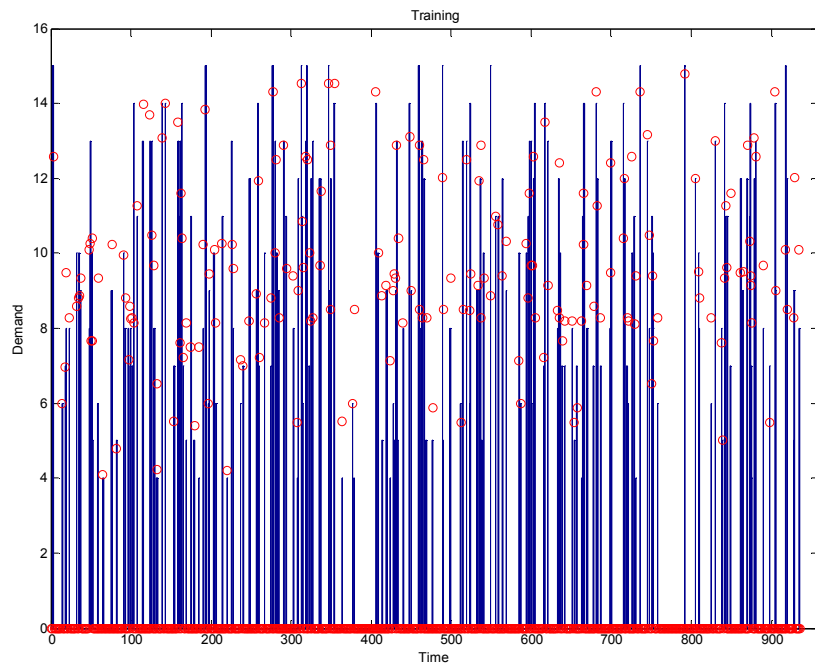


Figure 4: Training data with NN

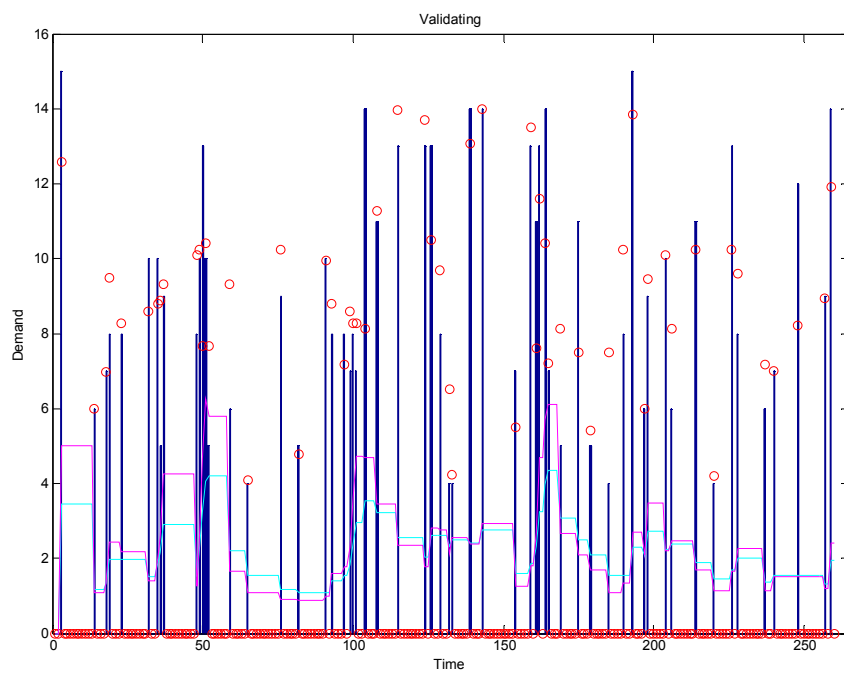


Figure 5: Validating data with NN, Croston alpha = 0.3 (cyan color) and Croston alpha = 0.5 (magenta color)

4. Conclusions

This paper successfully showed that the feed-forward back propagation network can be considered as a better alternative tool to conventional Croston method for predicting intermittent demand. Not using collected data sets, with randomly generated data, a comparison study illustrates that in general, proposed NN model can better perform in forecasting intermittent demand in term of two criteria MSE and MAE.

Acknowledgements

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