BETTER STATISTICAL FORECAST ACCURACY DOES NOT ALWAYS LEAD TO BETTER INVENTORY CONTROL EFFICIENCY: THE CASE OF LUMPY DEMAND

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ABSTRACT

Neural network (NN) modeling has been applied to forecasting of lumpy demand (Gutierrez, Solis, and Mukhopadhyay 2008; Mukhopadhyay, Solis, and Gutierrez 2012) and empirically compared with a number of well-referenced methods traditionally applied in studies on lumpy demand forecasting – simple moving average, weighted moving average with optimal weights, simple exponential smoothing, Croston's method, and the Syntetos-Boylan approximation. The overall superiority of NN over the other methods, in terms of forecast accuracy based on a number of scale-free error statistics, was demonstrated. However, demand forecasting performance with respect to standard accuracy measures may not translate into inventory systems efficiency. Applying a (T,S) inventory system, we consider fill rate (FR) as service criterion. We conduct simulation searches to find order-up-to levels required to meet a target FR of 0.90 or 0.95. We find that significantly higher levels of on-hand inventory are required when using the more statistically accurate NN forecasts.

Keywords: lumpy demand forecasting, forecast accuracy, scale-free error statistics, inventory control, simulation search

1. INTRODUCTION

Demand for an item is said to be *intermittent* when there are intervals during which no demand occurs. Demand is erratic when there are large variations in the sizes of actual demand occurrences. When demand is both intermittent and erratic, it is said to be *lumpy*. Intermittent or lumpy demand has been observed in both manufacturing and service environments – e.g., electrical equipment, jet engine tools and veterinary health products (Willemain, Smart, Schokor, and DeSautels 1994), the automotive industry (Syntetos and Boylan 2001, 2005), maintenance parts for aircraft, both commercial and military (Ghobbar and Friend 2002, 2003; Eaves and Kingsman 2004; Syntetos, Babai, Dallery, and Teunter 2009), electronic components (Gutierrez, Solis, and Mukhopadhyay 2008; Mukhopadhyay, Solis, and Gutierrez 2012), and professional electronics (Solis, Longo, Mukhopadhyay, Nicoletti, and Brasacchio 2014).

Syntetos, Boylan, and Croston (2005) proposed a scheme for categorizing demand into four classes (smooth, erratic, intermittent, and lumpy), as originally presented in the doctoral thesis of Syntetos (2001). The SBC scheme (for Syntetos, Boylan, and Croston) uses cutoff values of 0.49 for CV^2 (the squared coefficient of variation of demand sizes and 1.32 for *ADI* (the average inter-demand interval). SBC suggests $CV^2 < 0.49$ and $ADI > 1.32$ to characterize intermittent (but not very erratic) demand and $CV^2 > 0.49$ and $ADI > 1.32$ to characterize lumpy demand.

Simple exponential smoothing (SES) will adjust the demand forecast upward immediately after a demand occurs and downward if no demand occurs. Croston (1972) noted that, when demand is intermittent, therefore, the SES forecast results in a bias that places the most weight on the most recent demand occurrence. To address this bias in SES, he proposed a method for forecasting intermittent demand involving separate exponential smoothing of the nonzero demand sizes and the inter-demand intervals.

While Croston's method (CR) used a common exponential smoothing constant α, Schultz (1987) proposed separate smoothing constants, α_i and α_s, to be respectively used in updating estimates of inter-demand intervals and nonzero demand sizes. Eaves and Kingsman (2004) present a clear specification of CR involving these two smoothing constants.

A positive bias in CR, arising from an error in Croston's mathematical derivation of expected demand, has been reported by Syntetos and Boylan (2001). A correction factor of $(1-\alpha_i/2)$, applied to the CR estimator of demand, was suggested by Syntetos and Boylan (2005). This correction of the bias in CR has come to be known in the intermittent demand forecasting literature (Boylan and Syntetos 2007; Gutierrez, Solis, and Mukhopadhyay 2008; Mukhopadhyay, Solis, and Gutierrez 2012) as the Syntetos-Boylan approximation (SBA). We note that, while the correction factor is specified in terms of α_i, Syntetos and Boylan (2005) themselves apply SBA using a common smoothing constant $\alpha = \alpha_i = \alpha_s$. SBA has, in fact, been commonly implemented in this manner.

The above three methods (SES, CR, and SBA) are traditionally cited in the intermittent demand forecasting literature. As well, Syntetos and Boylan (2005) have evaluated a 13-period simple moving average (SMA) in comparison with SES, CR, and SBA.

Gutierrez, Solis, and Mukhopadhyay (2008) and Mukhopadhyay, Solis, and Gutierrez (2012) applied neural network (NN) modeling in forecasting lumpy demand. They used a multilayered perceptron trained by a back-propagation algorithm (Rumelhart, Hinton, and Williams 1988) using three network layers (as suggested by Xiang, Ding, and Lee 2005):

- One input layer for input variables,
- One hidden unit layer, and
- One output layer of one unit.

This NN architecture was applied to an industrial dataset consisting of 24 time series. Gutierrez, Solis, and Mukhopadhyay (2008) compared the forecasting performance of NN to those of the SES, CR, and SBA methods.

In addition to NN modeling, Mukhopadhyay, Solis, and Gutierrez (2012) evaluated one additional 'non-traditional' method for forecasting lumpy demand: a five-period weighted moving average with optimized weights (WMA5) determined by way of a standardized ordinary least squares regression with current period demand as target variable and the five most recent lagged period demands as predictor variables.

Mukhopadhyay, Solis, and Gutierrez (2012) initially used separate smoothing constants α_i and α_s, as proposed by Schultz (1987), in the application of CR and SBA. Apparently in view of the adjustment of the positive bias in CR by the correction factor of SBA, the latter was found by Mukhopadhyay, Solis, and Gutierrez (2012) to be consistently superior to the former for every single α_i and α_s combination tested. Furthermore, they did not observe any substantial improvement in forecast accuracy resulting from the use of separate smoothing constants α_i and α_s. As a result,

In this paper, therefore, we shall focus – as Mukhopadhyay, Solis, and Gutierrez (2012) did – on the comparative performance of the following four forecasting methods:

- SES
- SBA
- WMA5
- NN.

For intermittent demand, the use of low smoothing constant values in the range of 0.05-0.20 has been recommended (Croston 1972; Johnston and Boylan 1996). Syntetos and Boylan (2005) used the four α values of 0.05, 0.10, 0.15, and 0.20 for the SES, CR, and SBA methods. Gutierrez, Solis, and Mukhopadhyay (2008) and Mukhopadhyay, Solis and Gutierrez (2012) used these same four values.

This paper is organized as follows. In Section 2, we describe the industrial dataset, the partitioning of data into training and test samples, and error measures that have been used to assess forecast accuracy. In the next section, we briefly summarize the findings of Gutierrez, Solis, and Mukhopadhyay (2008) and Mukhopadhyay, Solis and Gutierrez (2012) in their empirical investigations of forecasting performance. In Section 4, we discuss results of our inventory control performance simulations. Section 5 is our concluding section.

2. DATASET, DATA PARTITIONING, AND FORECAST ACCURACY MEASURES

2.1. Dataset and Data Partitioning

Gutierrez, Solis, and Mukhopadhyay (2008) and Mukhopadhyay, Solis, and Gutierrez (2012) used actual demand data from an electronic components distributor operating in Monterrey, Mexico. The dataset involves 24 stock keeping units (SKUs), each with 967 daily demand observations. As a forecasting method, WMA5 applies to the dataset in terms of weekly demand over a 5-day work week.

All 24 SKUs exhibit lumpy demand, with values of CV^2 ranging between 9.84 and 45.93, and values of *ADI* between 2.63 and 3.28 (see Table 1). These CV^2 and *ADI* values are all clearly consistent with the SBC specification of $CV^2 > 0.49$ and $ADI > 1.32$ for lumpy demand.

Gutierrez, Solis, and Mukhopadhyay (2008) used the first 624 observations of the 967 daily demand observations in each of the 24 time series to 'train' the NN model (the *training* or *calibration* sample). The forecasting methods were then tested on the final 343 observations (the *test* sample). This generated an approximately 65:35 partitioning (65% training data and 35% test data).

In addition to the 65:35 partitioning, Mukhopadhyay, Solis and Gutierrez (2012) also applied an 80:20 split as suggested by Bishop (1995), as well as a 50:50 partitioning.

2.2. Forecast Accuracy Measures

Gutierrez, Solis, and Mukhopadhyay (2008) used the following three scale-free error statistics to compare forecast accuracy:

- mean absolute percentage error (MAPE),
- relative geometric root-mean-square error (RGRMSE), and
- percentage best (PB)

Mukhopadhyay, Solis and Gutierrez (2012) applied median relative absolute error (MdRAE) as a fourth scale-free measure.

Table 1: Basic Dataset Statistics

Series	1	2	3	4	5	6
Mean Demand	251.02	262.08	271.60	274.43	278.01	324.84
Std Dev of Demand	1078.80	985.19	1305.36	1221.31	1191.04	1387.20
z (% of Zero Demand)	69.6	67.2	67.3	65.9	64.3	63.8
CV^2	18.47	14.13	23.10	19.81	18.35	18.24
ADI	3.28	3.05	3.06	2.93	2.80	2.76
Series	7	8	9	10	11	12
Mean Demand	237.09	274.31	253.77	346.04	303.11	321.61
Std Dev of Demand	743.88	1134.55	959.19	1710.19	1229.80	1149.70
z (% of Zero Demand)	67.6	66.7	65.6	66.2	65.0	64.8
CV^2	9.84	17.11	14.29	24.43	16.46	12.78
ADI	3.09	3.00	2.90	2.96	2.86	2.84
Series	13	14	15	16	17	18
Mean Demand	299.15	296.07	288.78	305.81	228.74	352.32
Std Dev of Demand	1425.87	1321.28	1090.65	1257.98	889.07	1480.69
z (% of Zero Demand)	66.4	65.9	64.8	65.0	66.2	63.7
CV^2	22.72	19.92	14.26	16.92	15.11	17.66
ADI	2.98	2.93	2.84	2.86	2.96	2.75
Series	19	20	21	22	23	24
Mean Demand	322.98	355.48	328.70	394.84	314.33	410.00
Std Dev of Demand	1054.75	1609.05	1390.67	2675.95	1438.57	1929.56
z (% of Zero Demand)	61.9	65.3	64.2	67.0	64.3	67.3
CV^2	10.66	20.49	17.90	45.93	20.95	22.15
ADI	2.63	2.88	2.79	3.03	2.80	3.06

3. FORECASTING PERFORMANCE

Using MAPE, RGRMSE, and PB as error measures, Gutierrez, Solis, and Mukhopadhyay (2008) independently validated earlier findings (Syntetos and Boylan 2005) of the superiority of SBA over SES and CR. Moreover, they found that NN modeling, even under a relatively simple network topology, generally performs better than SES, CR, and SBA for the lumpy demand SKUs under investigation.

Mukhopadhyay, Solis, and Gutierrez (2012) added the following to the earlier evaluation:

- WMA5 as a forecasting method,
- MdRAE as a fourth scale-free error statistic, and
- 80:20 and 50:50 data partitions.

They found both 'non-traditional' methods (NN and WMA5) for forecasting lumpy demand to outperform the methods that are well referenced in the intermittent demand forecasting literature (SES, CR, and SBA). In particular, NN showed superior performance overall with respect to both MAPE and MdRAE as forecast accuracy measures, under all three data partitions (50:50, 65:35, and 80:20). What was found especially noteworthy was that SES and SBA, which have been traditionally applied to intermittent demand forecasting, did not appear as a 'best' method except in six of the 288 error statistic comparisons (24 SKUs × 4 error statistics × 3 partitions) that they reported.

4. INVENTORY CONTROL PERFORMANCE

Demand forecasting and inventory control performance have traditionally been examined independently of each other in the literature (Tiacci and Saetta 2009). Recognizing that demand forecasting performance with respect to standard accuracy measures may not translate into inventory systems efficiency, Solis, Mukhopadhyay and Gutierrez (2010) made an initial attempt to extend beyond the empirical investigation of forecasting performance reported in the earlier studies (Gutierrez, Solis, and Mukhopadhyay 2008; Mukhopadhyay, Solis, and Gutierrez 2012). The results of that first attempt, conducted by 'simulating on the dataset' in view of the difficulty in mathematically characterizing lumpy demand, were by-and-large inconclusive.

4.1. Demand Characterization

One of the issues in forecasting intermittent or lumpy demand is the assumption of a distribution of demand occurrence. Syntetos and Boylan (2006, p. 39) cited three criteria proposed by Boylan (1997) for assessing suitability of demand distributions:

- *a priori* grounds for modelling demand,
- flexibility of the distribution to represent different types of demand, and
- empirical evidence.

Syntetos and Boylan argued that compound distributions can represent demand incidence and demand size by separate distributions, and that the negative binomial distribution (NBD) is a compound distribution with variance greater than the mean, with "empirical evidence in its support." They declared the NBD "to meet all criteria" and accordingly selected NBD to represent intermittent demand over lead time (plus review period) in their stock control simulation model. Other studies (e.g., Boylan, Syntetos, and Karakostas 2008; Syntetos, Babai, Dallery, and Teunter 2009) have similarly conducted empirical investigations of stock control using the NBD to characterize intermittent demand over the lead time (plus review period), citing Syntetos and Boylan's (2006) declaration that the NBD "satisfies both theoretical and empirical criteria."

Use of the NBD to characterize demand may apply to intermittent (but not very erratic) demand. However, empirical investigation of lumpy demand datasets has shown that the NBD may not provide an acceptable approximation for many SKUs exhibiting lumpy demand. For instance, Solis, Longo, Mukhopadhyay, Nicoletti, and Brasacchio (2014) instead apply a two-stage approach to characterizing lumpy demand, where Stage 1 involves a uniform (continuous) distribution defined over the interval (0,1) and Stage 2 involves an NBD. While this two-stage alternative has been shown to fairly adequately characterize certain lumpy demand data, it unfortunately fails in the case of the 24 SKUs under consideration with their high degree of lumpiness.

Sani and Kingsman (1997) applied simulation on a dataset consisting of long series of daily demand data over five years for 30 low demand items. In view of the failure to mathematically characterize the 24 SKUs in the current lumpy demand dataset, our simulations of inventory control performance similarly take the form of a single run performed on the test sample (consisting of the final 343 observations for the 65:35 partition or the final 193 observations for the 80:20 partition).

4.2. Inventory Control System

A periodic review inventory control system has been recommended for intermittent demand (Sani and Kingsman 1997). An order-up-to (T,S) system, where T and S respectively denote the review period and the base stock (or 'order-up-to' level), has been used in recent intermittent demand forecasting studies that investigate both forecast accuracy and inventory control performance (Eaves and Kingsman 2004; Syntetos and Boylan 2006; Syntetos, Babai, Dallery, and Teunter 2009).

Eaves and Kingsman (2004) simulated a (T,S) system on actual demand data, aggregated quarterly, for 18,750 SKUs randomly selected out of some 685,000 spare parts for aircraft of the Royal Air Force of the UK. Forecast-based order-up-to levels S were determined as the product of the forecast demand per unit of time and the 'protection interval', T+L (where L is the reorder lead time). Implied average stockholdings were calculated using a backward-looking simulation assuming a common fill rate (or percentage of demand to be satisfied from on-hand inventory) of 100%. Among the five forecasting methods they evaluated (SES, CR, and SBA included), SBA yielded the lowest average stockholdings.

In the current study, we assume a (T,S) system with full backordering. For this preliminary report, inventory is reviewed on a weekly basis (T = 5) and the reorder lead time is three days (L = 3). The literature suggests a safety stock component to compensate for uncertainty in demand during the protection interval. For each SKU, we calculate s_{tr}, the standard deviation of daily demand over the training sample. We apply a 'safety factor' k to yield a safety stock level of $k \cdot s_{tr}$. The replenishment quantity q_t at the time of review is then given by

$$q_t = (T + L) \cdot F_t + k \cdot s_{tr} - I_t + B_t \,. \qquad (1)$$

where F_t is the forecast calculated at the time of review t, and I_t and B_t are, respectively, the on-hand inventory and backlog.

Two of the most commonly used service level criteria for inventory systems (Silver, Pyke, and Peterson 1998) are:

- Probability of not stocking out in a given period, and
- Fill rate (FR)

FR is noted to have considerably more appeal for practitioners. We consider target FRs of 0.90 and 0.95 (or 90% and 95%), as in Syntetos and Boylan (2006). Using spreadsheet modeling, we conduct simulation searches to find, for each of the four forecasting methods under evaluation (SES, SBA, WMA5, and NN), the safety factor k needed to meet the target FR.

4.3. Simulation Results

We first report on simulation results arising under a 65:35 data partition with a target FR of 95%. In Figure 1, we graphically compare the average on-hand inventory levels arising from use of the four forecasting methods. While Mukhopadhyay, Solis, and Gutierrez (2012) found both NN and WMA5 to outperform SES and SBA (as reported in Section 3), average on-hand inventory levels appear to be higher overall for WMA5 and NN.

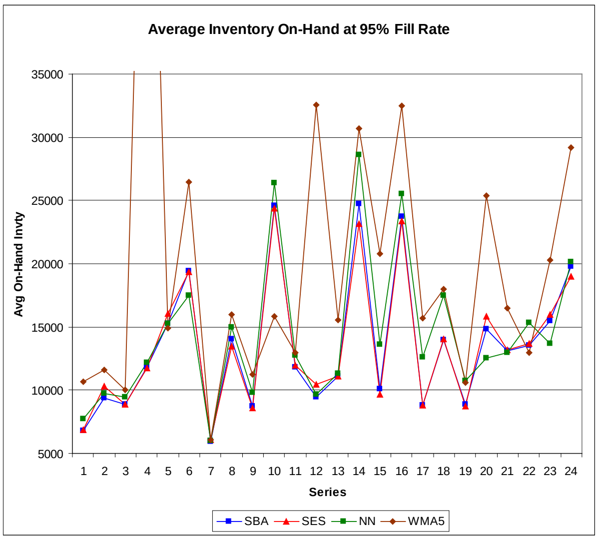

Figure 1: Average Inventory On-Hand with a 95% Fill Rate Under 65:35 Data Partitioning

SES yields the minimum average inventory on-hand for 11 of the 24 SKUs, SBA for six, NN for four, and WMA5 for three. We index the average inventory on-hand using SBA as base (SBA = 100), and those indices are summarized in Table 2. Using a t-test of the hypothesis that mean index = 100, the right-hand tailed test is highly significant for both NN/SBA (p-value = 0.0040) and WMA5/SBA (p-value = 0.0075) but not significant for SES/SBA (p-value = 0.2311).

The average backlogs resulting from a 95% target FR, arising under a 65:35 data partition, are similarly indexed using SBA as base. Resulting indices are summarized in Table 3. Using a t-test of the hypothesis that mean index = 100, the test is not significant for SES/SBA, NN/SBA, and WMA5/SBA.

We likewise summarize the simulation results arising under an 80:20 data partition with a target FR of 90%. The average on-hand inventory levels are graphically presented in Figure 2. In this case, NN yields the minimum average inventory on-hand for 10 of the 24 SKUs, SES for seven, SBA for four, and WMA5 for three.

Similarly, if average inventory on-hand is indexed using SBA as base, the overall average indices are 101.0 for SES/SBA, 106.7 for NN/SBA, and 141.1 for WMA5/SBA. The right-hand tailed t-test of the hypothesis that mean index = 100 is highly significant for WMA5/SBA (p-value = 0.0025), significant for

NN/SBA (p-value = 0.0409), and not significant for SES/SBA (p-value = 0.2095).

Table 2: Indices of Average Inventory On-Hand with a 95% Fill Rate Under 65:35 Data Partitioning, Using SBA as Base

	Index		
Series	SES / SBA	NN / SBA	WMA5 / SBA
1	100.3	113.0	155.9
2	109.6	104.0	123.4
3	99.6	106.3	112.9
4	99.6	103.4	605.5
5	105.0	99.9	97.7
6	99.8	90.3	136.4
7	102.3	101.4	102.1
8	95.7	106.4	113.6
9	98.3	112.3	128.7
10	99.2	107.4	64.5
11	101.4	107.9	109.9
12	110.4	102.3	343.8
13	99.6	101.6	139.9
14	93.5	115.6	124.0
15	96.0	135.4	206.6
16	98.3	107.7	137.0
17	99.6	143.1	177.8
18	100.5	125.2	128.8
19	98.1	120.7	119.1
20	106.8	84.6	171.5
21	100.6	98.8	126.0
22	101.3	113.4	95.9
23	103.4	88.6	131.4
24	96.1	101.8	147.3
Average	100.6	108.0	158.3

Table 3: Indices of Average Backlog with a 95% Fill Rate Under 65:35 Data Partitioning, Using SBA as Base

	Index		
Series	SES / SBA	NN / SBA	WMA5 / SBA
1	103.9	126.8	144.3
2	100.5	88.0	94.6
3	102.3	89.1	127.7
4	99.9	103.4	99.9
5	104.0	106.9	114.4
6	100.0	100.0	100.0
7	101.4	114.9	65.9
8	100.0	100.2	91.9
9	104.5	69.7	75.1
10	103.8	91.1	120.3
11	104.8	86.6	119.9
12	103.3	71.2	109.2
13	109.4	103.4	105.8
14	100.1	102.4	108.7
15	108.1	64.9	118.0
16	102.2	98.0	136.1
17	93.0	110.5	95.9
18	99.2	92.7	104.6
19	105.0	77.9	64.9
20	100.0	99.3	100.3
21	100.9	107.0	84.9
22	97.8	104.3	70.8
23	86.2	110.5	64.3
24	99.8	99.8	104.1
Average	101.2	96.6	100.9

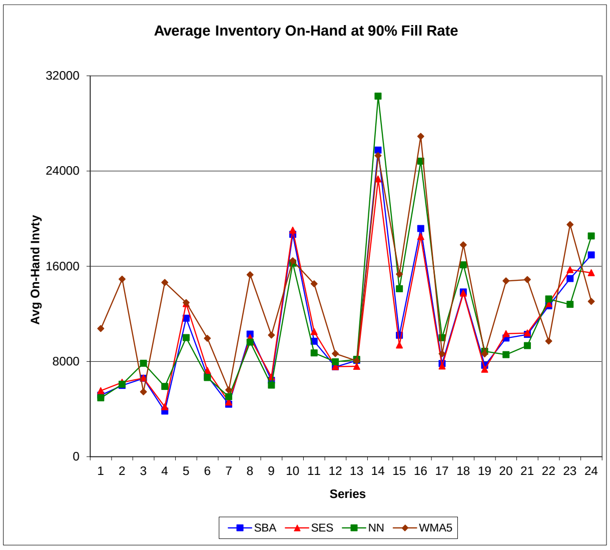

Figure 2: Average Inventory On-Hand with a 90% Fill Rate Under 80:20 Data Partitioning

Average backlogs and corresponding indices for a 90% target FR arising under an 80:20 data partition show overall average indices of 100.9 for SES/SBA, 96.8 for NN/SBA, and 102.7 for WMA5/SBA. Using a t-test of the hypothesis that mean index = 100, the test is not significant for SES/SBA, NN/SBA, and WMA5/SBA.

5. CONCLUSIONS AND FURTHER WORK

Owing to the difficulty in mathematically characterizing lumpy demand distributions, particularly with the degree of lumpiness found in the industrial dataset currently under consideration, we applied simulation on the dataset in the current work. This was possible due to the length of the time series (967 periods), albeit not quite as rigorous as in simulation studies involving mathematically specified demand distributions.

Gutierrez, Solis, and Mukhopadhyay (2008) found that NN modeling, even under a relatively simple network topology, generally performs better than SES, CR, and SBA for the 24 lumpy demand SKUs under investigation (as reported in Section 3). Mukhopadhyay, Solis, and Gutierrez (2012) reported the 'non-traditional' NN and WMA5 methods to outperform SES and SBA (as also reported in Section 3).

We conducted simulation searches associated with target fill rates of 90% and 95%. With average on-hand inventory using SBA as base, the indices for WMA5/SBA and even for NN/SBA are significantly above 100, indicating that average on-hand inventory levels are higher overall for WMA5 and NN.

In the current study, we find support for earlier assertions that demand forecasting performance with respect to standard accuracy measures may not translate into inventory systems efficiency. In particular, an NN model was found to outperform the SES and SBA methods in performance with respect to a number of scale-free traditional accuracy measures, but appears to be inferior when it comes to inventory control performance.

We appear to have generated evidence to support the assertion that, at least for items exhibiting a fairly high degree of demand lumpiness, statistical forecast accuracy does not necessarily lead to better inventory control efficiency.

Further work remains in terms of simulation searches that have yet to be conducted.

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